Electric Vehicle Charger Placement Optimization in Michigan: Phase II - Urban

March 7, 2020

Prepared for:
Michigan Department of Environment, Great Lakes, and Energy (EGLE)
Constitution Hall
525 West Allegan Street
P.O. Box 30473
Lansing, MI 48909-7973

Prepared by:
Michigan State University

Principal Investigator:
Dr. Mehrnaz Ghamami
Assistant Professor
Civil and Environmental Engineering
428 S. Shaw Lane, East Lansing, MI 48824
Phone: (517) 355-1288, Fax: (517) 432-1827
Email: ghamamim@msu.edu

Authors

Dr. Mehrnaz Ghamami (PI)
Assistant Professor[1]
Phone: (517) 355-1288, Fax: (517) 432-1827
Email: ghamamim@msu.edu

Dr. Ali Zockaie (Co-PI)[1]
Assistant Professor
Phone: (517) 355-8422, Fax: (517) 432-1827
Email : zockaiea@msu.edu

Dr. Steven Miller (Co-PI)[2]
Director of Center for Economic Analysis
Phone: (517) 355-2153
Email: mill1707@msu.edu

Mohammadreza Kavianipour[1]
Doctoral Researcher
Email: kavianip@egr.msu.edu

Fatemeh Fakhrmoosavi[1]
Doctoral Researcher
Email: moosavi@msu.edu

Harprinderjot Singh[1]
Doctoral Researcher
Email: singhh24@msu.edu

Farish Jazlan[1]
Doctoral Researcher
Email: farish@egr.msu.edu

MohammadHossein Shojaei[1]
Doctoral Researcher
Email: shojaeim@msu.edu

[1] Department of Civil and Environmental Engineering, Michigan State University, 428 S. Shaw Lane, East Lansing, MI 48824

[2] Department of Agricultural, Food, and Resource Economics, Michigan State University, Morrill Hall of Agriculture, 446 W Circle Dr Room 88, East Lansing, MI 48824 U.S.

ACKNOWLEDGMENTS

The Michigan State University researchers would like to acknowledge the Michigan Department of Environment, Great Lakes, and Energy (EGLE) for sponsoring this research, understanding the timeliness of the topic, and supporting this unique approach to allocating electric vehicle charging infrastructure. We are grateful to the EGLE team for arranging stakeholder meetings that enabled the team to obtain the necessary information for the analysis. Lastly, but not least, we thank the many stakeholders listed below for their engagement, willingness to share data and insights, and their valued partnership.

EGLE
- Robert Jackson
- Lisa Thomas

Michigan Department of Transportation

Auto Companies
- Ford Motor Company
- General Motors
- Toyota

Transmission and Utility Companies
- American Transmission Company
- Cherryland Electric Cooperative
- Consumers Energy
- DTE Energy
- Great Lakes Energy Cooperative
- Indiana Michigan Power
- ITC Transmission Company
- Lansing Board of Water and Light
- Michigan Electric Cooperative Association
- Michigan Municipal Electric Association
- Wolverine Power Cooperative

Charging Station Companies
- ChargePoint
- Greenlots

Cities and Communities
- City of Ann Arbor and Ecology Center
- City of Grand Rapids
- City of East Lansing
- City of Marquette
- City of Kalamazoo

National Organizations
- Electrify America
- National Association of State Energy Officials

Electric Vehicle Drivers & Owners

This work was supported by the Department of Energy and Energy Services under Award Number EE008653.

Table of Contents

List of Tables

List of Figures

EXECUTIVE SUMMARY

The primary purpose of this report is help local units of government develop a plan to support the use of plug-in electric vehicles (EV), and develop policies and strategies that support investment into public charging infrastructure. Michigan Department of Environment, Great Lakes, and Energy (EGLE) has funded the development of a comprehensive approach, including analytical models considering applied constraints, to find the optimum investment scenario for each urban area and has supported it through a series of stakeholders' meetings. Researchers at Michigan State University led this effort by developing and executing the modeling framework.

This study builds on a previous study conducted by the same research team at Michigan State University supported by EGLE (former MI Energy office) which located DC fast chargers across the state of Michigan supporting long-distance (highway) trips of EVs in 2030. During the highway study it became evident that there is a need for a framework to optimaly locate charging infrastructure in urban areas. This report presents the study approach and results of the optimization model for locating DC fast chargers in different urban areas in Michigan for the urban trips of EV users in the state by the year 2030. Note that level 2 chargers are not the focus of this study, however, the impact of these chargers, located at shopping centers or work places, is considered in the state of charge estimator function, as an input to the optimization framework. The results for major urban areas in Michigan are presented in more detail, while the results for smaller urban areas are presented in a more aggregate manner, depending on the availability of data for these urban areas.

Through a series of stakeholder meetings, different scenarios with different battery and charger technologies were suggested and investigated for this study. The suggested battery energy levels are 70 kWh and 100 kWh, and power levels of 50 kW and 150 kW are considered for chargers. Also, the winter scenario is selected for this study, as the number of urban trips is known to remain relatively constant seasonally, while the reduced battery performance during the cold seasons requires more chargers and charging stations. Table 1 shows a summary of the findings for different urban areas sorted by their travel demand. The details of the scenarios and requirements are available in the report.

Table 1. Summary of the findings for different urban areas and different scenarios, sorted by travel demand

Urban Areas	Number of Stations	Number of Chargers	Total Infrastructure Cost (Million dollar)	Average Charging and Queuing Delay (min)
Marquette	4-5	8-19	1.13-1.39	4.24-15.63
Muskegon	6-9	18-48	2.27-2.72	3.94-15.13
Ann Arbor	3	10-29	1.74-2.02	4.01-15.35
Kalamazoo	7-12	19-57	2.47-3.26	3.79-14.63
Flint	8-14	26-73	3.47-4.62	3.85-14.90
Saginaw	17-27	45-123	5.70-7.17	4.11-15.82
Lansing	10-16	33-89	4.62-5.91	3.83-14.74
Grand Rapids	12-17	47-132	6.09-7.31	3.79-14.65
Detroit	42-62	233-636	30.09-38.41	3.97-15.40

This study suggests a list of locations for charging stations and the number of chargers at each location, with an approximate cost of building such network for major urban areas in the state of Michigan. The tables and figures of these results are available in the results section, as well as the appendices. For smaller urban areas in Michigan the minimum number of chargers and charging stations is suggested in this report for each urban area. The major findings of this study are listed below:

1. Even though the battery size (driving range) is one of the main decisive factors in EV infrastructure configuration to support the intercity trips of EV users. The battery size is not a significant factor in electric vehicles charger placement to support the urban trips of EV users. This is due to the shorter distance of the trips in urban areas, compared to that of the intercity trips.
2. Increasing the power of chargers provides stations with a higher throughput and thus less number of chargers (and charging stations) are required to support the urban trips of EV users.
3. It is less costly to build a network of 150 kW chargers than 50 kW chargers. Building these chargers also reduces the charging and waiting time. However, if the vehicles cannot accept the 150-kW power level, longer delays would be experienced, while all the trips still would remain feasible.
4. The total length of the roadways, vehicle miles traveled, and number of daily trips generated are the main factors affecting the number of charging stations. This demonstrates the fact that the travel demand, including the distance traveled, and the size of the city are factors that affect the number of charging stations required for urban areas.
5. The factors affecting the number of chargers include the number of daily generated trips and the total length of the roadways. It is worth noting that most of the smaller cities require less than two chargers per station to serve the EV demand, however, for redundancy purposes at least two chargers per station are recommended.
6. The suggested numbers and locations are based on a predicted 6 percent market penetration rate in 2030. It is suggested that the city planners start building the network of charging stations in increments and track the utilization rate at each location before proceeding with full deployment. Detailed analysis for the annual increments can be done for each urban area per request.

An optimization-based modeling framework is designed and proposed in this study to find the location of charging stations and number of chargers for the major urban areas in the state of Michigan, listed as: Muskegon, Ann Arbor, Kalamazoo, Flint, Saginaw, Lansing, Grand Rapids, and Detroit. As all of the major urban areas are located in lower peninsula, for equity purposes, Marquette, the largest city in the upper peninsula is added to the list for detailed analysis. Aggregate level regression models are developed to find the number of charging stations and chargers in the smaller cities, with limited data availability, such as: Menominee, Sault Ste. Marie, Escanaba, Houghton, Traverse City, Battle Creek, Jackson, Port Huron, and Holland. The models proposed in this study can be used for other cities based-on availability of data as the need arises.

INTRODUCTION

There is an increasing pattern in the adoption of electric vehicles during the past few years. However, the rate of this increase varies among different states. This rate is significant for Michigan, but still it is smaller than the U.S. average (Atlas EV Hub, 2018). This increasing pattern, among other factors, is due to energy efficiency and low emission production of Electric Vehicles (EVs) (Eberhard and Tarpenning, 2006; Philippe Crist, 2012). The market share of alternative fuel vehicles, such as EVs is affected by a variety of factors, including but not limited to fuel cost, purchase price, and demographics (Eppstein et al., 2011; Lin et al., 2014; Lin and Greene, 2010, 2011; NRC, 2013; Shafiei et al., 2012). However, recent studies have revealed that a dense network of charging stations is the most important factor leading to an increase in the adoption of EVs (Nie et al., 2016).

Due to the limited range of EVs, refueling stations have been vastly studied to support the long-distance (intercity) trips of these vehicles (Ghamami et al., 2016, 2019a; Nie and Ghamami, 2013). Since the average length of daily trips of EV users is less than the average driving range of an electric vehicle on a single charge, the urban trips of EV users have attracted less attention. It is worth noting that by the increasing market share of EVs, not all EV owners are going to have access to a home charger or a charger at workplace, and many users (depending on their arrival and departure time) are not going to have enough time to fully charge their car batteries. Thus, there is an increasing need for Direct Current (DC) fast charging stations to support the urban trips of EV users.

The Michigan Department of Environment, Great Lakes, and Energy (EGLE) initiated the investment in an analytical approach to find the optimum location of chargers for the urban trips of the EV users. This study aims to introduce a framework for urban charging planning. This approach considers the urban trips of EV users, electric grid infrastructure, and costs associated with building a network of charging stations to find the optimum investment strategy, while ensuring the feasibility of urban trips for EVs in Michigan.

EGLE facilitated a series of stakeholder meetings with Metropolitan Planning Organizations, communities, utility companies, charging station companies, the automotive industry, and the State of Michigan departments. These meetings enabled the data collection process and refinement of the assumptions for the analytical approach. The analytical approach proposed in this study is unique to the best knowledge of the research team. This approach includes simulating the trips of EV drivers, using the data from travel surveys and planning models, and incorporating the simulated trips of EV drivers in the optimization framework to find the best investment strategy.

For the remainder of this report, the problem statement, literature review, methodology including the modeling framework, and the solution approach are presented, which are followed by the city selection procedure and data requirements for each city. Finally, the results for each urban area are presented.

PROBLEM STATEMENT

This study aim to provide a guide for palnning urban charging infrastructure. The length of daily urban trips is usually smaller than the average driving range (on a fully charged battery) of an EV. However, not all EVs start their trip fully charged. EV users might not have access to chargers at home or workplaces or they might forget to plug-in their cars. Furthermore, depending on arrival and departure time, EVs might not get fully charged overnight using a level II charger. More importantly, in order to alleviate the EV users' range anxiety and reduce the uncertainty in EV trips, there is an immediate need for DC fast chargers (level 3 chargers) in urban areas. This study seeks to find the optimum location of charging stations and the number of chargers for urban trips of EV users in the state of Michigan. Note that level 2 chargers are not the focus of this study, however, the impact of these chargers, located at shopping centers or work places, is considered in the state of charge estimator function, which is elaborated in the following sections. The trips of users are modeled using a dynamic traffic simulation tool, and the charging behavior and the state of charge of the users are tracked within the modeling framework. The main aim of this study is to aid city planners to ensure that the urban trips of EV users are feasible throughout the state, while minimizing the system cost. This cost consists of infrastructure investment cost, including charging station and charger costs, and the experienced delay by users, including detour, charging, and waiting time in queues. It is also recommended that the city planners build the network gradually and track and compare utilitization rate and energy consumption level at fully functional stations and chargers. This phase of the project seeks to answer the following questions:

- Where to deploy charging stations in urban areas of Michigan to support the EV travels in 2030?
- How many chargers should be provided at each charging station?
- What is the cost associated with building the required infrastructure for each urban area?
- What is the expected delay for the considered scenarios in major urban areas?

LITERATURE REVIEW

Increasing vehicle miles traveled (VMT), and the associated emissions have all led the car industry toward EVs (Dong et al., 2014; He et al., 2013). EVs remove the on-road emission, and if accompanied by green energy initiatives, they can mitigate air pollution significantly. Limited range, insufficient supporting infrastructure, and long charging times have hindered the acceptance of the EVs in the market (He et al., 2013; Nie and Ghamami, 2013). Although some current EV models can exceed the range of 300 miles per charge, most of the EVs still barely can be compared with conventional vehicles (CV) in terms of the driving range. It is worth noting that battery performance of EVs decreases in cold weather, which further reduces the range of EVs (Krisher, 2019). To increase the adoption of EVs, providing enough supporting infrastructure is the key factor (Nie et al., 2016).

Many data-driven studies have investigated the location of charging infrastructure for EVs. Based on the travel surveys data, conducted by Metropolitan Travel Survey Archive, a framework is available to locate charging stations using each trip endpoint, distance, purpose, starting time, and ending time (Andrews et al., 2012). In another study, Dong et al. (2014) used travel data of 275 households and minimized the number of trips not being fulfilled by electricity as the source of energy, using an activity-based model. Another study uses trajectory data of taxis in Beijing to identify hotspots, which are defined as candidates to be equipped with charging stations (Cai et al., 2014). This study is then extended by proposing an optimization model to select among the hotspots to maximize the VMT on electricity (Shahraki et al., 2015). Taxi GPS data is also used to develop an optimization model for the location of charging stations using spatial-temporal demand coverage data (Tu et al., 2016). Another study, using taxi trajectories, minimizes the infrastructure investment cost considering the congestion at charging stations (Yang et al., 2017). In another approach, using the average national data, an optimization model is developed minimizing the infrastructure cost, while serving the EV charging demand in workplaces (Huang and Zhou, 2015). The above-mentioned models can be applied to fleet vehicle (i.e. taxis or buses), but are not suitable for private EVs due to the limited availability of GPS data.

Therefore, based on the origin-destination (OD) demand models, the travel behavior can be modeled and used to allocate charging infrastructure. A group of studies considers the travel pattern independent of charging infrastructure, and as a function of traffic assignment (Berman et al., 1992; Hodgson, 1990; Kuby and Lim, 2007, 2005; Lim and Kuby, 2010; Upchurch et al., 2009; Zockaie et al., 2016). There are also other studies accounting for the impact of desired facilities on the traffic assignment (Bai et al., 2011; Hajibabai et al., 2014; He et al., 2013, 2018; Huang et al., 2015; Riemann et al., 2015). However, in large scale networks that have thousands of links and nodes, the problem becomes computationally demanding. Therefore, researchers favor the fixed travel patterns in large scale networks.

Urban trips of EV users have been less of an interest to researchers due to their limited travel distances. However, the importance of these studies has become more evident over the years (Baouche et al., 2014; Cavadas et al., 2015). There is a variety of approaches for serving the urban trips of EV users. In one approach, the trips of EV users are modeled based on travel surveys (Baouche et al., 2014). In another approach, the charging stations can be located based on the activities (Kang and Recker, 2009; Nie et al., 2016).

To find the optimal location of charging facilities, different objectives have been investigated. Minimizing only the investment cost (Li et al., 2016; Mak et al., 2013; Mirhassani and Ebrazi, 2013; Yang et al., 2017) or minimizing the number of charging stations (He et al., 2016) will not provide the optimum solution; as the delay to access chargers may increase significantly due to the limited infrastructure availability. Minimizing only the access time (Nicholas et al., 2004) or minimizing only travel time in urban areas (He et al., 2015) may also cause budgetary concerns. However, minimizing the system cost (Chen et al., 2017; Ghamami et al., 2019a; Hajibabai et al., 2014; Nourbakhsh and Ouyang, 2010; Zhu et al., 2018) can make a balance between cost of charging infrastructure and monetary cost of users' delay. Therefore, the required infrastructure would be determined based on infrastructure investment, while keeping the EV trips feasible and users' delay reasonable.

This study aims to introduce a framework for urban charging planning. Urban networks usually include many nodes and links, which can make the traffic assignment computationally demanding. Therefore, using a dynamic traffic assignment framework and the origin-destination demand, the trajectories for all trips are extracted. Using the large-scale traffic simulation results the charging behaviors of EV users are investigated. Vehicle trajectories in need of charge, which are identified based on the initial state of charge and the required energy to complete their trips, are considered as inputs to the optimization model. This model seeks a charging station configuration to serve the trips of EV users. Thus, the main contribution of this study is to ensure feasibility of simulated EV trips considering the impacts of queuing and detours on the location of charging stations and the number of chargers required at each station.

METHODOLOGY

The first step to the modeling and solution framework proposed in this study is data collection. The data required for this study includes origin-destination travel demand (OD demand), road network information, land use information, land cost, electricity provision cost, and charging station and charger costs and specifications. Users' trips are then simulated using a dynamic traffic simulation tool. The main inputs to the simulation are OD demand and road network information. The main outputs of the traffic simulation are trip trajectories and the dynamic skims including travel times and distances for every OD-pair and all departure time intervals. Unlike the intercity trips, which are well-planned and start with fully charged batteries, the urban trips are not usually well-planned, and users might start with any state of charge. Therefore, a state of charge simulator is developed, which works based on the trip purpose, and land use at the trip origin. This simulator determines the initial state of charge for each trip trajectory. Then, all the above-mentioned information is used as inputs to the optimization model.

The modeling framework proposed in this study considers the limited range of EVs and ensures that every EV trip is feasible by providing supporting charging infrastructure, while minimizing the total cost of charging infrastructures and the monetary value of total delay experienced by EV users. The model differentiates between different candidate locations that can be equipped with charging stations based on land acquisition cost and electricity provision cost at each location. The constraints considered in this model include flow conservation equations, charging station allocation, tracking the state of fuel, trip feasibility, and charging and queuing delay in stations.

The problem is formulated as a mixed-integer programming with nonlinear constraints, which is known to be NP-hard. As the commercial solvers cannot solve such problems, it is decomposed into two sub-problems. The first sub-problem locates the charging stations and assigns EVs to them by minimizing the charging station cost and the monetary value of detour and charging time experienced by EVs. The second sub-problem finds the optimum number of chargers required at each of the selected charging stations while minimizing the charger cost and users' waiting delay. The vehicles assigned to charging stations are the output of the first sub-problem and the input to the second sub-problem.

The first sub-problem is solved using a commercial solver, CPLEX, in the AMPL platform.

This model can solve the problem efficiently for small to medium-size cities. However, as the size of the city grows, the efficiency of using commercial solver, in terms of memory requirement and solution time, decreases significantly. Therefore, a metaheuristic algorithm is required to solve the problem for large-scale networks. In this study, Simulated Annealing (SA) is used to design an algorithm for solving the problem for large-scale networks. Simulated annealing is known to provide a good solution in a reasonable time for facility location problems (Ghamami et al., 2019a; Zockaie et al., 2016). The output of the first sub-problem is the selected locations for building charging stations, which support urban trips of EVs while ensuring that all EVs can fulfill their trips by tracking the state of charge. As the charging stations might not be exactly located along the users' routes with minimum travel time, EVs need to deviate from their initial route to access the charging station. This model minimizes the detours required to access the charging stations along with considering land acquisition and electricity provision costs.

The second sub-problem optimizes the number of chargers required at each station. As the EV allocation to charging stations is decided in the first sub-problem, the incoming flow (potential queue) at each station and the chargers' cost determine the number of chargers in this step. The proposed sub-problem captures the trade-off between the cost of providing needed chargers and users' delay using a value of time factor, which calculates the monetary value of the experienced delay. Obtaining the estimated arrival time of EVs to charging stations from the first sub-problem, a dynamic queuing approach is implemented in this sub-problem to account for the stochasticity associated with trajectories.

As mentioned earlier, the main inputs to the model include OD demand, road network information, land use information, land cost, and electricity provision cost. This detailed information is not always available, especially for small urban areas. Thus, regression models are calibrated and validated using the results of the proposed optimization model for multiple cities with available data. The regression models can be used for small urban areas to determine the number of charging stations and chargers and the total investment cost; however, the aggregate level regression models do not specify the exact location of charging stations. Figure 1 illustrates the general framework and different steps of this study.

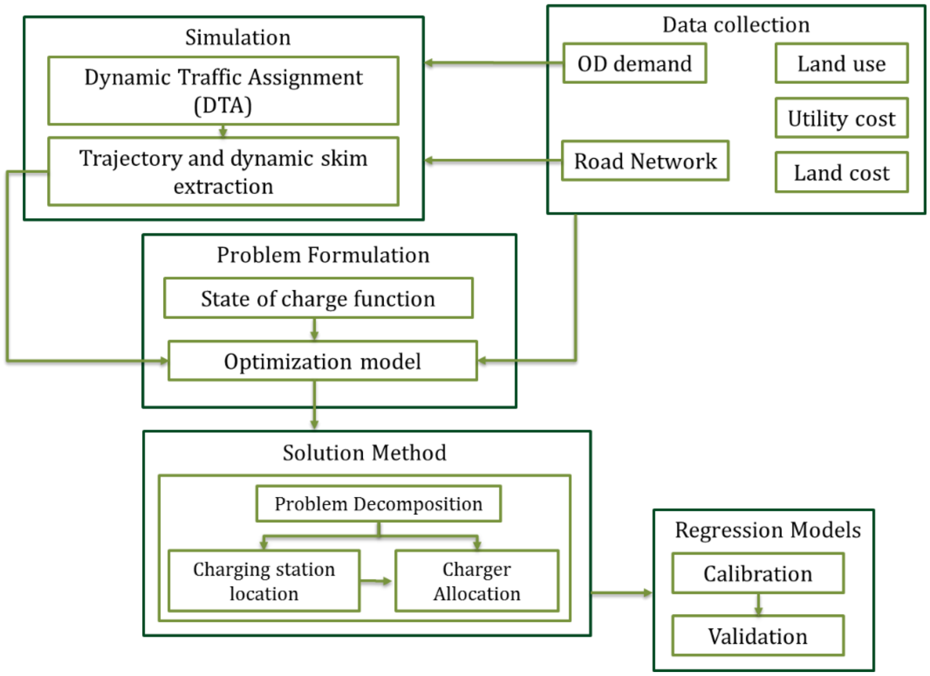


Figure 1. General research framework

Traffic Simulation

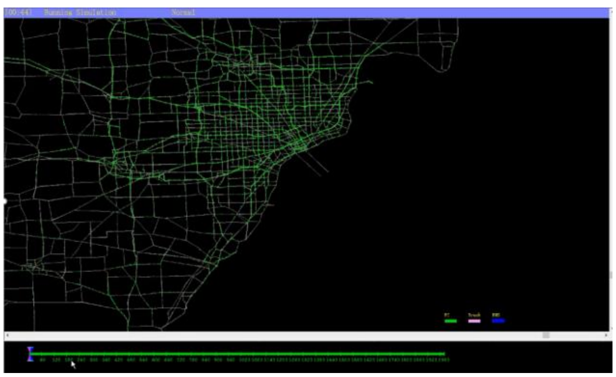
Traffic state and congestion level affect the route choice of EV users as well as non-EV drivers. In addition, trip chains of EV users should be considered in the charger placement problem. In this project, road traffic of the state-wide Michigan network is simulated and the trajectories of EV trips (vehicle traveled paths on the road as a function of time), happening daily at different cities, are extracted. Traffic simulation is a mathematical application of transportation systems through a computer tool that is utilized for planning, operational, or design purposes. Visual demonstration of present or future scenarios is an important application of the traffic simulation in transportation systems. Therefore, in order to predict the time-dependent charging demands for different locations using the trajectories of EV trips, which are assigned randomly as 6% of all trips in the selected cities sub-networks, state-wide Michigan traffic is simulated through a traffic simulator. In general, transportation models can be classified into three classes in terms of the level of details: microscopic, mesoscopic, and macroscopic. To have a fast execution and easy calibration, the mesoscopic simulation tool of DYNASMART-P is used for the purpose of this study (Jayakrishnan et al., 1994). For traffic flow propagation, meso-simulation tools move individual entities (vehicles) according to traffic flow relations coming from macroscopic speed-density relations.

Using the dynamic traffic assignment, DYNASMART-P supports many different transportation planning and operational decisions. This tool combines dynamic traffic assignment models and traffic simulation models. In addition, DYNASMART-P provides the capability to model traffic flows in a network resulting from the decisions of adaptive users seeking for the optimal paths en-route over the planning horizon. Thus, it overcomes many of the limitations of tools used in current planning practice. DYNASMART-P takes road network data and system configurations as the inputs, and generates individual vehicles based on time-dependent OD demands. Once all vehicles are generated, they will be assigned to the paths with the minimum generalized cost and the user equilibrium process is executed. Finally, the trajectories of all vehicles, including electric vehicles, along with all optimal paths from origins to destinations are reported as the outputs of the software. The EV trajectories are then extracted from all vehicles to be used in an optimization framework to find the optimal charging infrastructure configuration minimizing the total system cost. Note that a portion of vehicles, either electric or not, is assumed to be adaptive and may use alternate routes in case of congestion or gridlock on initially selected routes. These vehicles are aware of the current traffic conditions in different regions of the network by having access to real-time information. Five categories of data are required for DYNASMART-P as below.

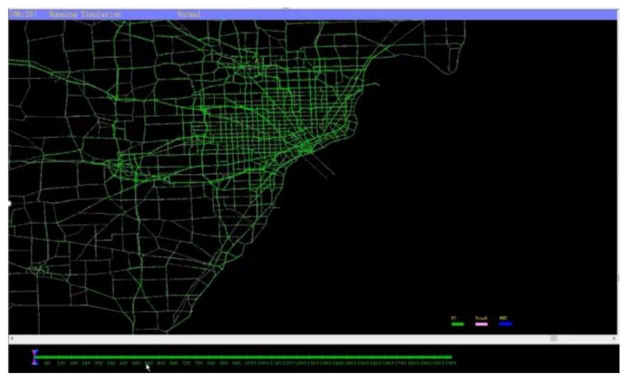
- Network data: the main input in this category is a file containing the state-wide network nodes and links information. Michigan Department of Transportation (MDOT) provided a TransCAD file of the Michigan network, which is converted to a readable format by DYNASMART-P. Figure 2 depicts the configuration of the state-wide Michigan network.
- Control data: the control data file represents the control types of all Michigan network nodes (intersections) and the phasing details of the signalized intersections.
- Demand data: the static demand matrix is provided on the daily basis by MDOT. Hourly factors are multiplied into the static demands to convert them into a time-dependent OD demand matrix.
- Traffic flow relations: the speed-density curves, specific for the Michigan network are calibrated using the data of installed loop detectors by MDOT along Michigan freeways.
- Scenario and system data: these two inputs are critical for scenario analysis and defining the settings of the simulation runs.

Figure 2. State-wide Michigan network

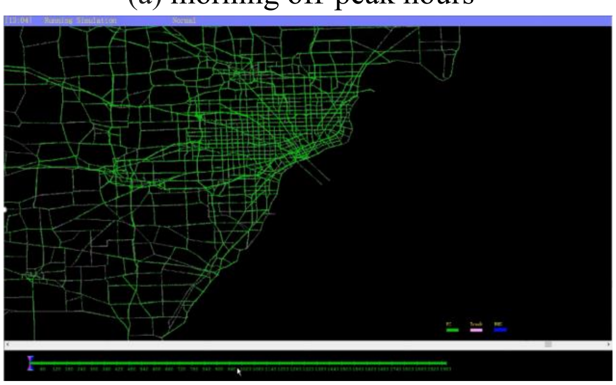
Given the state-wide Michigan network, illustrated in Figure 2, and the prepared input files, the simulation is executed using DYNASMART-P and the vehicles are assigned to the routes with the least generalized costs. Using the results of the traffic assignment, the trajectories of trips originating from the selected cities are extracted for each city. Note that 6% of all trips inside each city are assumed to be driven by EVs. These trajectories are then used as inputs to the charging simulator to estimate their charging needs and find the EVs that need to be recharged. As an illustration of the traffic simulation results, the snapshots of the simulated vehicles inside Detroit, resulted from the traffic simulation and assignment using DYNASMART-P, are shown for four different times (early morning, morning peak period, afternoon peak period, and off-peak period of night) in Figure 3. Each green dot in this figure represents a vehicle moving along a network link; thus, the intensity of green dots indicates the level of traffic congestion on the road.



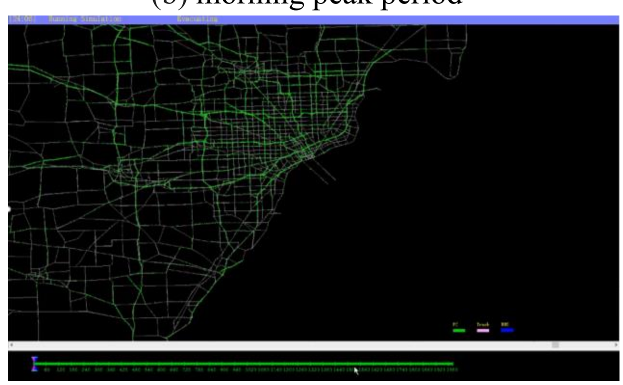
(a) morning off-peak hours



(b) morning peak period



(c) afternoon peak period



(d) off-peak period of night

Figure 3. Simulation results (vehicles distributed in the network) for the Detroit metropolitan area

State of Charge Simulator

Unlike intercity trips, which are considered as stand-alone trips, urban trips are usually part of a chain of trips and not usually as preplanned as the intercity trips. Therefore, EV users may start their urban trips with any state of charge in contrast to intercity trips, which are highly likely to be initiated with fully charged batteries. The trip origin and departure time affect the initial state of charge for EVs. In this study, a simulation tool is developed to estimate the EVs' charging behavior. This simulation is based on a survey conducted by the Michigan Department of Transportation in

2016 (Wilaby and Casas, 2016). This survey presents the time-dependent trip purposes in Michigan, which are shown in Figure 4. The time-dependent trip purposes and the land use information are then used to estimate the origin and purpose of each trajectory probabilistically. This study distinguishes the trips starting from home based on their residential type. It considers a higher initial state of charge for single-family residential areas compared to multi-family residential areas. Furthermore, some workplaces are providing charging facilities for their employees. Therefore, EVs starting their trips from workplaces are assumed to have a higher chance of initiating their trips with a higher initial state of charge. In this study, using a normal distribution, the charging simulation accounts for the stochasticity inherent in users' charging behavior both on the initial state of charge and their desired state of charge. The desired state of charge is defined as the level of charge EVs expect to have by the end of their trips. The difference between the desired state of charge and the initial charge plus the charge spent en-route to reach the destination is the total charge required for each trajectory. If this value is positive, then the EV needs to recharge; otherwise, the trajectory (vehicle) does not need charging and would not be considered in the modeling framework for the optimization purpose. Considering a normal distribution, Table 2. shows the mean and standard deviation for initial state of charge of vehicles departing from different land uses before 12 PM. It is assumed that the vehicles' state of charge reduces during the day due to multiple trips they make. These reductions are reflected by reducing the initial state of charge by 0.1 for trips starting between 12 PM and 5 PM, and by 0.2 for trips starting after 5 PM. Moreover, a normal distribution with a mean of 0.15 and a standard deviation of 0.1 is considered for the state of charge that EVs expect to have upon their arrival to their destination.

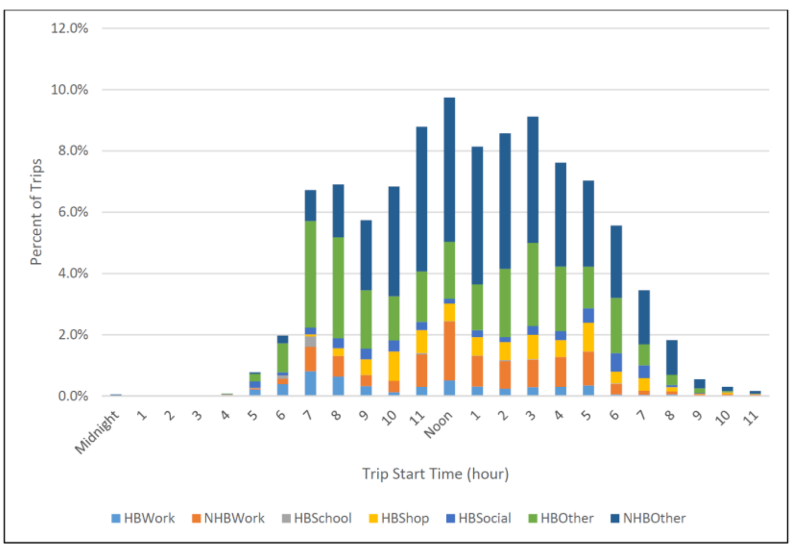


Figure 4. Person trips by start time (hour) and trip purpose (Wilaby and Casas, 2016)
(HB: Home-Based, NHB: Non-Home-Based. Home-Based trips are trips with home being either the start or end point of the trip. For example: HBWork trips are trips with home at one end and work at the other end.)

Table 2. Initial state of charge of vehicles departing before 12 PM for different land uses

	Initial state of charge			
Battery (kWh)	70		100	
	Mean	SD	Mean	SD
Home- single family	0.75	0.05	0.7	0.05
Home- multi family	0.5	0.2	0.6	0.2
Work	0.6	0.2	0.65	0.3
Other	0.55	0.3	0.6	0.3

Optimization Model

The objective function of the proposed optimization model for the problem of interest in this study minimizes the total system cost, which includes the infrastructure investment cost on charging stations and chargers as well as the total delay experienced by EV users. As the problem associated with this objective function is highly nonlinear, it is decomposed into two sub-problems. The objective function of the first sub-problem minimizes the investment in charging stations, charging delay, and detour delay. Then, the second sub-problem minimizes the cost of chargers and the delay experienced by EV drivers in charging stations.

In this section, the main objective function is formulated, which can be decomposed into two objective functions (for each sub-problem). The road network consists of a set of zones ($i \in I$). Each electric vehicle ($j \in J$) has a trajectory that its information is derived from the dynamic traffic simulation, including the information on origin-destination, route choice, departure time, trip length, and travel time. A set of times ($\tau \in T$) reflects when vehicles arrive at charging stations. This discrete set allows the model to capture the visiting flow to stations during each time period.

The objective function below minimizes the investment cost (charger, grid, construction, land, etc.) and user charging, detour, and waiting time costs. Each parameter of the model is defined in Table 3.

$$\min \sum_{i \in I} (C_i^s x_i + C_i^p z_i) + \gamma (\sum_{i \in I} \sum_{\tau \in T} \pi_i^\tau + \sum_{j \in J} TTd_j) \quad (1)$$

Table 3. Model variable descriptions and definitions

Variable	Description	Unit/Value
C_i^s	Charging station cost	\$/day
C_i^p	Charger cost	\$/day
γ	Value of time	\$/hr
π_i^τ	Delay time for waiting and refueling at charging stations	hour
TTd_j	Detour travel time required for charging	hour
x_i	Charging station decision variable	Build or Not $\in \{0,1\}$
z_i	Number of chargers	Integer Number

The objective function consists of two main terms. The first term, infrastructure investment cost, includes the fixed cost of building charging stations and the variable cost of providing chargers. The cost of charging stations includes the cost of facilities required for the installation of chargers and the electricity provision cost. The cost of chargers consists of the chargers' cost (equipment, activation cost, etc.), construction cost, and land cost. The second term in the objective function represents the monetary value of the delay experienced by EV users. It includes the charging and queuing delay experienced by EV users captured by π_i^τ and the required detour for each EV user to access the charging station, which is captured by TTd_j. These delays are multiplied by γ, which is the value of time and is assumed to be \$18/h, to provide the monetary value of the delay time. The decision variables are the zones that should be equipped with charging stations and the number of chargers at each station.

The objective function is followed by a set of constraints. These constraints include tracking the state of charge, flow conservation, detour time, and queuing constraints. For tracking the state of fuel, it is considered that EVs cannot charge more than their capacity. Therefore, EVs cannot charge in stations where their required charge is more than their available capacity. Furthermore, EVs can only charge in a charging station that is within their current range. The detour time for each trajectory is calculated considering the difference between the initial trip duration and the trip duration in which the vehicle visits the charging station.

Solution Approach

As mentioned earlier, the optimization model is a mixed-integer problem with non-linear constraints. Due to the computational complexity, the commercial solvers cannot provide solutions efficiently for these types of problems, especially for large-scale networks. In this study, using a decomposition technique, the problem is transformed into two sub-problems. The first sub-problem locates the charging stations in the network minimizing the cost of charging stations, detour, and charging delay. The second sub-problem finds the number of required chargers minimizing the cost of chargers and the queue experienced by EV users. A solution framework is presented for each of these sub-problems.

The first sub-problem determines the location of charging stations. The objective function of this problem is as follows:

$$\min \sum_{i\in I}(C_i^s x_i) + \gamma(\sum_{\tau\in T}\sum_{\theta\in T}\sum_{i\in I}\sum_{j\in J} Q_{ij}^{\tau\theta} R_{ij}^{\theta} + \sum_{j\in J} TTd_j) \tag{2}$$

The decision variable in the above objective function is x_i, which is equal to 1 if there is a charging station and 0 otherwise. This objective function along with its constraints form a mixed-integer program with linear constraints. The commercial solvers, e.g. CPLEX, can be incorporated to solve these problems. However, as the problem size grows, the computational requirement increases exponentially. Therefore, a metaheuristic approach is also implemented for large case studies. The metaheuristic algorithm implemented in this project is based on Simulated Annealing (SA). An SA-based algorithm usually involves two steps. First, the feasible set of integer solutions is searched to find a neighbor solution for the current solution. Then, the algorithm compares the objective functions of the current and the new solution. If the neighbor solution improves the objective function, the neighbor solution replaces the current solution and becomes the new current solution. However, if the objective function is not improved (a worse solution), the probability of replacing the current solution is a function of the relative difference between the objective function values of the neighbor and the current solution. The probability is gradually reduced as the solution process proceeds through the iterations of the algorithm. This probability is close to zero by the end of the iterations meaning that the worse solution will not be accepted anymore. This mechanism prevents the solution from getting trapped in local optima. Then, the trajectories are assigned to an available station minimizing their total detour.

The second sub-problem finds the optimum number of chargers in charging stations. Based on the first problem, trajectories assigned to each charging station are known. These trajectories reach to charging stations having a temporal distribution with AM and PM peaks. Based on the availability of chargers, they either charge upon their arrival or wait in queue for an available charger. This sub-problem makes a trade-off between providing more chargers and letting the users to wait in queue for an available charge. The objective function of this sub-problem, which minimizes the charger costs and the queuing delay experienced by EV users at charging stations, is as follows:

$$\min C^p z_i + \gamma \sum_{\tau \in T} y_i^\tau \bar{W}_i^\tau \tag{3}$$

The decision variable in this sub-problem is the number of chargers. y_i^τ represents the number of EVs entering the charging station while the queuing delay is captured in $\bar{W}_i^\tau$. The objective function value can be estimated based on some assumptions on arrival and service rates. Assuming a uniform arrival rate and service rate, the queuing behavior can be modeled based on a deterministic queue modeling approach (Zukerman, 2013). Then, the objective function along with its constraints forms a mixed-integer problem with nonlinear constraints. Since the objective function is strictly convex and the constraints are convex, the proposed problem can be solved with the Golden-section search technique, which is designed to find the extreme value of a function in a pre-defined interval as its domain (Kavianipour et al., 2020). In addition, commercial solvers such as Knitro can be also incorporated to solve this problem. The deterministic queuing assumption provides the minimum number of chargers required to support the EVs' charging. However, once the arrival rate of vehicles to charging stations is lower than the service rate, then the arrival process can be modeled as a Poisson distribution with exponential service rate distribution. Therefore, the M/M/k queuing formulations should be used to model the users' queuing behavior (Zukerman, 2013). The average queue size of the M/M/k system is convex with respect to the traffic flow (Grassmann, 1983). Therefore, the optimum value of the objective function can be calculated using the Golden-section search technique. It is worth noting that the M/M/k equations are applicable where service rate is greater than arrival rate. If the arrival rate is greater than the service rate, only the deterministic approach is applicable.

Regression Models

The proposed optimization model needs detailed data on road network information, spatial-temporal distribution of trips, electricity provision cost, and land cost. However, this detailed information may not always be available and often harder to obtain for smaller urban areas depending on the resources available. Thus, two regression models are developed to estimate the number of chargers and the number of charging stations for areas with limited data availability. The results of the optimization model provide inputs for the regression models calibration. These models estimate the number of chargers and charging stations for any city based on aggregate measures without requiring detailed information.

A variety of linear and non-linear regression models were estimated considering different combinations of input variables (aggregate measures as independent variables) to estimate the total number of charging stations and chargers (dependent variables) needed in urban areas. The estimated regression models are compared based on the following parameters:

1. ***p*-value**: The p-value, also known as the calculated probability, investigate the truth of the null hypothesis. A p-value of less than 0.05 indicates that the null hypothesis can be rejected with enough evidence. This value explains the statistical significance of a particular variable in the model and the model as a whole. The statistically insignificant models and models with insignificant variables are not considered.
2. **R-squared and Adjusted R-squared values**: The R-squared value explains the goodness-of-fit for each regression model. The adjusted R-squared take into account the number of variables in the model and is used to compare models with different numbers of independent variables. The higher the adjusted R-squared, the better the model. The equations for estimating R-squared and adjusted R-squared are as follows (Listen Data, 2019):

$$R^2 = 1 - \frac{SS_{res}}{SS_{tot}} \tag{4}$$

$$R^2_{adjusted} = 1 - \frac{(1 - R^2)(N - 1)}{N - p - 1} \tag{5}$$

   Where SS_{res} is the sum of squares of residuals. A residual is the difference between the observed value and the predicted value of the dependent variable by the model at a particular data point. SS_{tot} is the total sum of squares, which measures the total variation in the data. It is given by the sum of squares of the difference between the observed value of the dependent variable at the data points and the mean (average) of all the observed values in the dataset. The terms 'N' and 'p' are the number of data points and the number of independent variables considered in the model, respectively.
3. **RMSE**: It is the root mean square error of the observed value and the predicted value. This parameter explains the overall deviations of all predicted values by the model from the observed values in the dataset. The smaller this error term, the better the model is in predicting the dependent variable. The RMSE for a dataset is estimated as follows (Barnston, 1992):

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N}\left(y_i^{obs} - y_i^{pred}\right)^2}{N}} \tag{6}$$

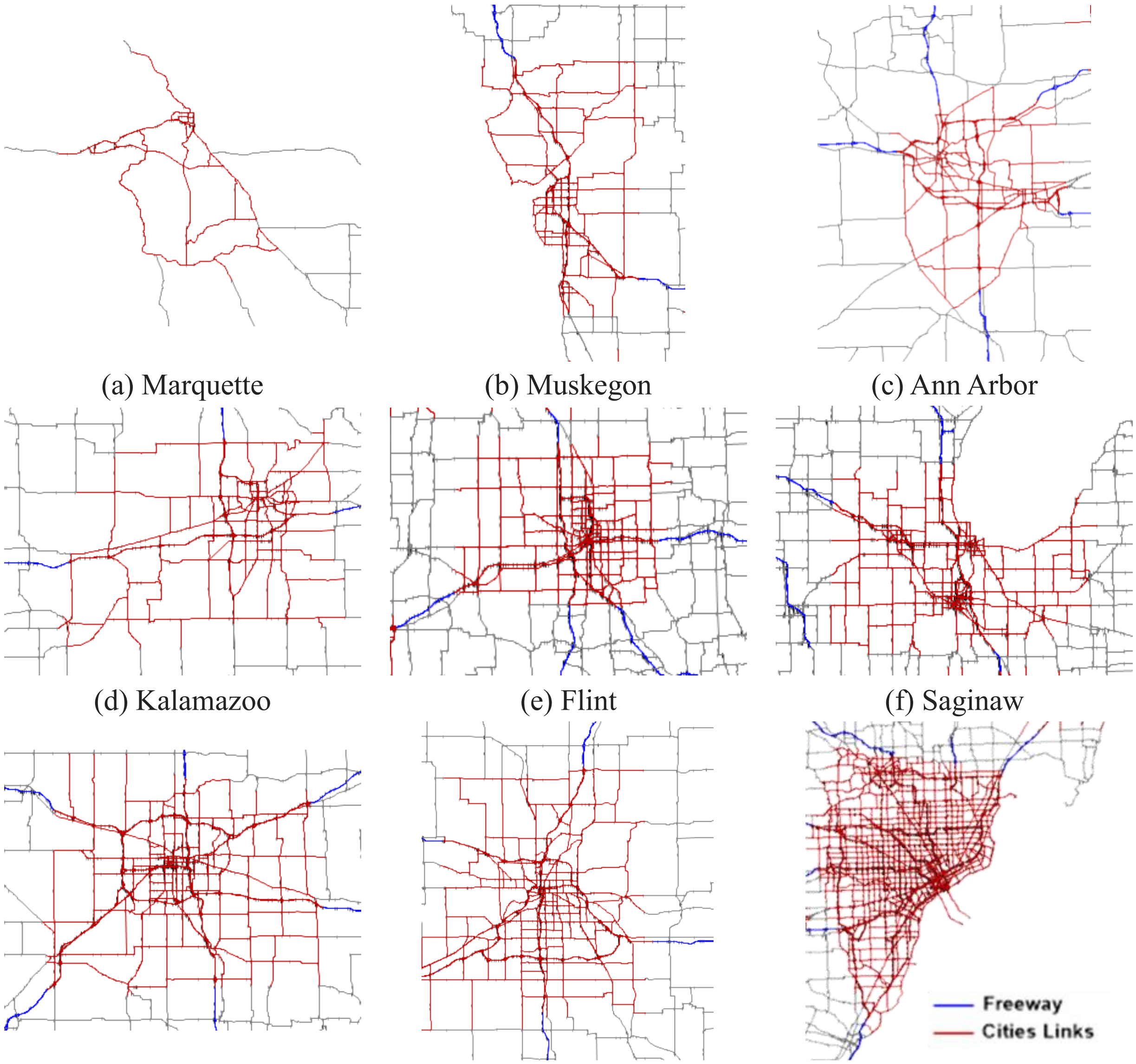
In which y_i^{obs} and y_i^{pred} are the observed value (from the dataset) and the predicted value (by the regression model) of the dependent variable at a particular data point 'i', respectively. The term 'N' is the total number of data points.

CITY SELECTION

Using the state-wide Michigan network, different information including the number of zones, generated demand, lane length, and estimated traveled miles are extracted for each candidate city. Among the candidate cities, those with sufficient network details and generated trips are selected for the EV charger placement analyses. In addition, the city with the highest generated demand in the Upper-Peninsula in Michigan, Marquette, is selected for the analysis. A data summary of the candidate cities is provided in Table 4. The selected cities for the detailed EV charger placement analysis are shown in bold fonts in this table. The regression models are used to find the charger and station counts for other cities in this table. In addition, the schematic views of the extracted sub-networks for the cities analyzed with the optimization model are illustrated in Figure 5.

Table 4. Data Summary for the candidate cities of the EV charger placement analysis sorted based on the generated demand

Cities /Parameter	Number of Nodes	Number of Zones	Generated Demand	Lane Length (mi)	Vehicle Miles Traveled (per day)
Menominee	9	6	41,297	54	166,799
Sault Ste. Marie	42	6	61,412	133	229,042
Escanaba	43	14	103,491	260	479,245
Houghton	76	31	113,403	626	558,063
Marquette	62	21	178,741	336	931,957
Traverse City	53	13	226,264	212	1,124,123
Battle Creek	182	25	245,167	406	1,385,189
Jackson	259	24	274,350	461	1,542,840
Port Huron	255	30	296,516	918	2,717,248
Holland	204	20	373,233	525	2,279,219
Muskegon	387	52	535,443	916	3,161,057
Ann Arbor	413	36	624,618	789	3,894,950
Kalamazoo	369	55	712,796	1128	4,085,052
Flint	694	84	985,411	1557	6,760,436
Saginaw	783	116	1,054,842	2726	7,122,931
Lansing	896	91	1,086,242	2030	7,183,037
Grand Rapids	1031	82	1,726,732	2045	10,447,668
Detroit	5461	301	8,185,778	8776	52,293,864



(a) Marquette (b) Muskegon (c) Ann Arbor

(d) Kalamazoo (e) Flint (f) Saginaw

(g) Lansing (h) Grand Rapids (i) Detroit

Figure 5. Sub-networks of the selected cities for EV charger placement analysis with the optimization model

DATA COLLECTION

The optimization framework and the dynamic traffic simulation require data including origin-destination travel demand, Michigan road network, land use information, charging station and charger costs, site acquisition costs, utility provision costs, and vehicle and user characteristics. This section explains the details of obtaining each of these data sets.

Michigan Road Network and Origin-Destination Travel Demand

The Michigan road network is provided to the research team by MDOT. This road network consists of 37,125 links, including 11,516 freeways or highways, 20,742 arterials, and 4,867 ramps, as well as 16,976 nodes, including 4,237 signalized intersections. The road network, presented in Figure

2, is provided to the research team in TransCAD format. MDOT also provided origin-destination travel demand information. MDOT conducts travel surveys periodically. The results of these surveys are inputs to the MDOT travel planning models, which provide the demand table for about 3,000 traffic analysis zones (TAZs) for a weekday in fall. Given these data, the road networks of different candidate cities are extracted from the state-wide road network.

Land Use Information

The initial state-of-charge (i-SOC) depends on the probability of users having access to an available charger. The accessibility of chargers is currently highly correlated with land-use. Thus, land-use information was obtained from MDOT and also from different cities and communities. The land-use information obtained from the different sources were compared and in case of inconsistencies, the city/community data was prioritized over the MDOT data. The land-use categories of interest in this study include residential (single or multi-family), industrial, commercial, and other.

Charging Station and Charger Costs

The charging station and charger costs were provided by different charging station companies, such as Greenlots and ChargePoint. The chargers considered here have either a CHAdeMO or SAE combo connector. The chargers are assumed to charge one vehicle at a time, requiring one parking spot. Thus, the charger cost used in the current study includes charger cost, land cost, validation, and activation costs. The charging station costs include site acquisition, utility upgrade, electrical panel and switchgear, engineering and design, permitting, and project management costs.

Site acquisition costs and utility costs at each candidate location, which are discussed in more details in the following subsections, are obtained from cities/communities and utility companies, respectively. Thus, the approximate values provided by charging station companies for site acquisition cost and utility provision costs are replaced with the values estimated by cities/ communities and utility companies, respectively.

Site Acquisition Costs

Site acquisition costs are obtained from cities and communities. The cities and communities had a variety of approaches in preparing this data. The most common approach was using the assessors' data to find the land cost by square feet and apply the unit land cost to the area required for each of the charging stations.

Utility Provision Costs

Michigan Public Service Commission website was used to find the utility companies at each candidate point. The utility companies with jurisdiction at the candidate points are:

- Alger Delta
- DTE Energy
- ConsumersEnergy
- Grand Haven Board of Light and Power
- Great Lakes Energy
- Indiana Michigan Power

- Marquette Board of Light and Power
- Upper Peninsula Power Company
- Midwest Energy
- Tri-county
- Lansing Board of Water and Light

It is worth noting that the basis for utility cost calculations vary from location to location or among different utility companies depending on the resources available at each company. Utility companies either reported the cost at the exact candidate point (center of the TAZ), the average cost over the TAZ, or an approximate average cost over an area with a few TAZs. The costs were requested for 100 kVA, 500 kVA, 1,000 kVA, and 2,000 kVA load levels. However, utility companies reported that the load ranges listed do not affect the electricity provision cost. For the locations with no data, interpolation and extrapolation of the data available in Phase II (the current project), as well as averaging data available from Phase I of the project, are adopted.

The electricity provision costs reported by the utility companies include but are not limited to conduit from the transformer to the meter enclosure, meter enclosure, protective equipment, and conduit and conductor from the meter enclosure to the charging station.

Vehicle and User Characteristics

This study aims to introduce a framework for urban charging infrastructure planning. For this purpose, this study suggests networks of charging stations for urban areas in Michigan. The design of such system requires information about vehicles and users' characteristics. The main reason is that the system is designed for the users to operate their vehicles. The details of such characteristics are described as follows:

Battery Range and Performance Variation

Driving range of EVs determines the charging behavior of EV users. Thus, through stakeholder meetings with automobile manufacturers, the EV battery capacities for the upcoming year of 2030 were investigated. They suggested 50kWh batteries for small cars, 70-80 kWh for mid-size vehicles, and 100-120 kWh for large vehicles. Therefore, in this study, battery sizes of 70 kWh and 100 kWh were tested for a variety of scenarios. Also, a battery performance of 3.5 miles/kWh for summer with a 30% reduction factor for winter weather conditions was suggested.

Electric Vehicle Market Share

The EVs' adoption rate has been increasing in the past decade. The expected market share of EVs for the state of Michigan in 2030 is 6%, as shown in Figure 6, which is predicted by Midcontinent Independent System Operator (MISO) (Dana Lowell, Brian Jones, 2017).

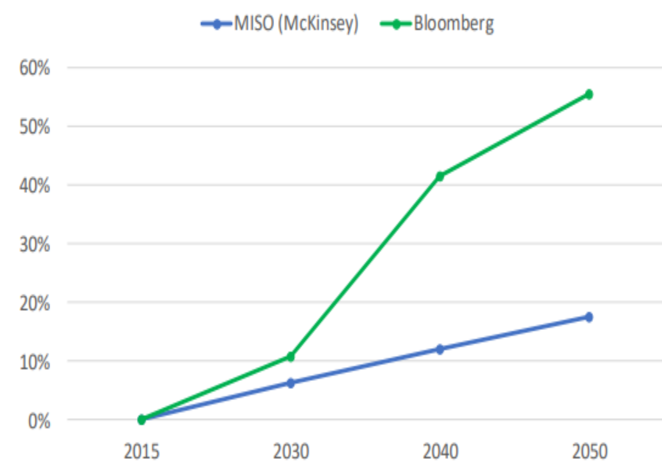


Figure 6. EV Market share projections (Dana Lowell, Brian Jones, 2017)

Scenarios

This study is designed to find the optimum location of charging stations and the number of chargers required at each station for the target year of 2030. As planning for the future involves uncertainty, different scenarios are tested to find the optimal charging configuration. Based on the different scenarios tested in Phase I of EV Charger Placement Study, the winter scenario, in which the battery performance reduces by 30%, requires more charging stations and chargers among different seasons (Ghamami et al., 2019b). Also, it was shown that a bare-bone charging network designed for winter can provide trip feasibility for EV users during summer as well. It is worth noting that urban travel demand, unlike the intercity travel demand, is expected not to change significantly over different seasons. Similar to phase I, two battery types with capacities of 70 kWh and 100 kWh are considered in the current study. Two charging power of 50 kW and 150 kW are also considered to charge EVs. Different combinations of these assumptions provide four scenarios. Table 5. presents these scenarios.

Table 5. Specifications of the considered scenarios for the target year of 2030

Scenario	1	2	3	4
Battery Capacity (kWh)	70	100	70	100
Charger Power (kW)	50	50	150	150

RESULTS AND DISCUSSION

This section details the project results. For each urban area, a total of four scenarios are investigated. Table 6 to Table 14 provide information on the inputs to the model in the first four rows and summarize the outputs of the model in the next six rows. The model input consists of battery size, charging power, the number of traffic analysis zones, and the number of EV trips. The output data includes the number of charging stations, the total number of chargers, total charging delay, station cost, charger cost, and total investment cost. Figure 7 to Figure 42 show the charging infrastructure configuration for all tested scenarios for the listed major urban areas. The red dots in these figures represent charging stations, while the blue dots show candidate locations that have not been selected to be equipped with charging stations. The size of each red dot represents the recommended number of chargers at each station. It is worth noting that the recommended number of chargers are to be installed in the entire traffic analysis zone (represented by the red dot) not at the specific latitude and longitude listed. The size of the traffic analysis zones increases as the population density decreases. Comparing the scenario results for the listed major urban areas, scenarios 3 and 4, with 150 kW chargers, provide a lower investment cost compared to the other two scenarios. Furthermore, they provide lower average charging and queuing times. In these scenarios, fewer chargers are required at each station due to a higher throughput rate resulted from the higher charging power level. Lastly, although the per-unit cost of 150 kW chargers is higher than the per-unit cost of 50 kW chargers, the total infrastructure costs are lower for the high-tech scenarios, due to less number of required charging stations and chargers.

As a large portion of the demand for the city of Ann Arbor travels to and from outside the city and its vicinity boundaries, additional analysis for this city is performed to include the demand traveling to and from outside the city and its vicinity boundaries (Appendix A).

Results of the Optimization Model for Charging Station Placement and Charger Counts for Major Urban Areas

City of Marquette

Table 6. Scenario results for the city of Marquette: charging stations, chargers, required investment, and charge time

Scenario	1	2	3	4
Battery size (kWh)	70	100	70	100
Charging power (kW)	50	50	150	150
Number of zones	21	21	21	21
EV trips per day	4,753	4,753	4,753	4,753
Number of stations	5	4	4	4
Number of chargers	19	16	8	9
Station cost (Million dollar)	0.70	0.56	0.68	0.68
Charger cost (Million dollar)	0.68	0.57	0.63	0.70
Total infrastructure cost (Million dollar)	1.37	1.13	1.31	1.39
Average charging and queuing delay (min)	11.48	15.63	4.24	5.29

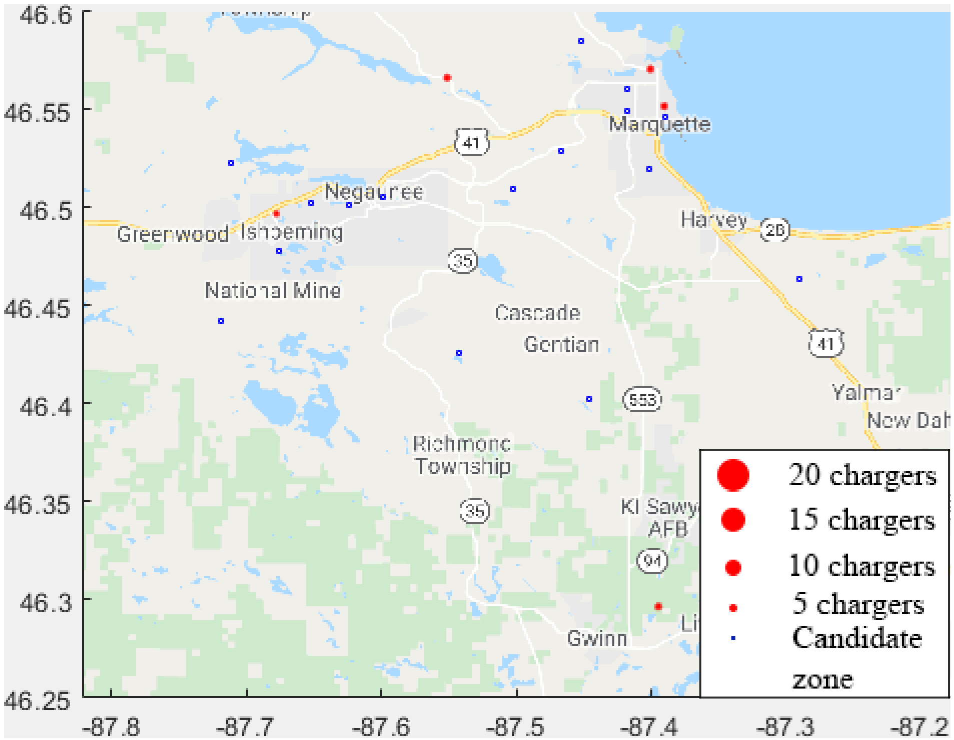


Figure 7. 70 kWh battery-50 kW charger configuration for the city of Marquette

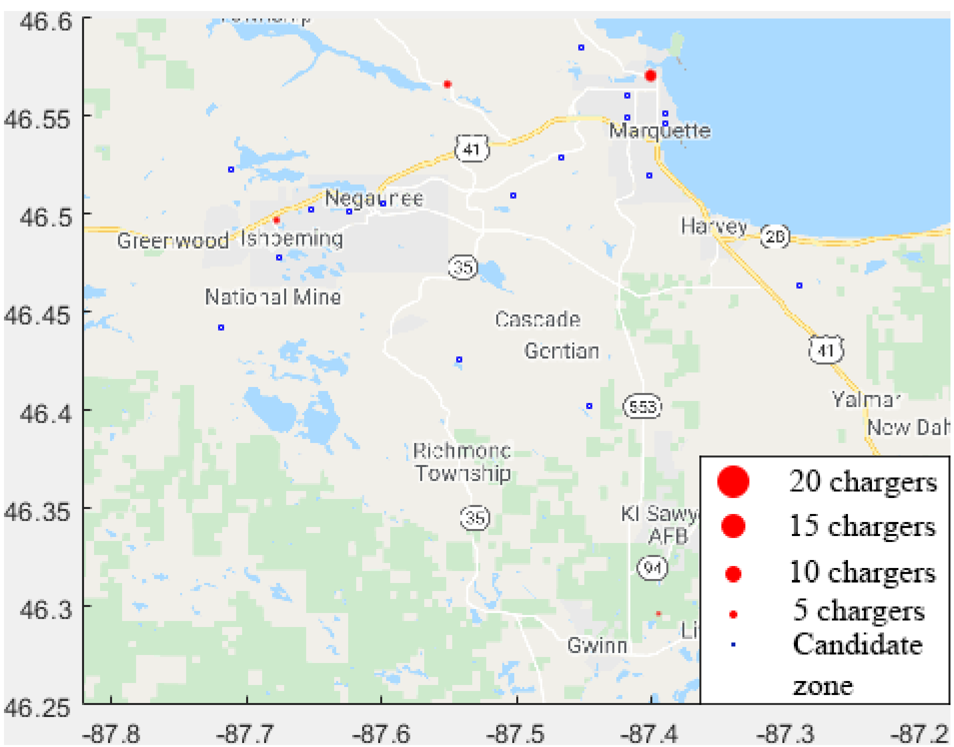


Figure 8. 100 kWh battery-50 kW charger configuration for the city of Marquette

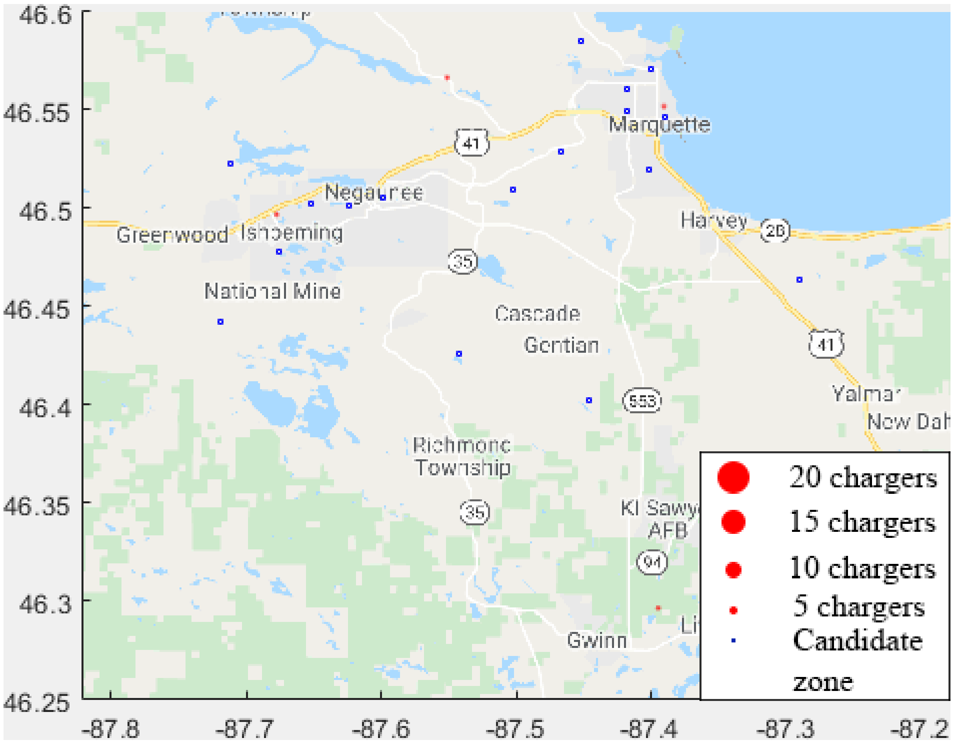


Figure 9. 70 kWh battery-150 kW charger configuration for the city of Marquette

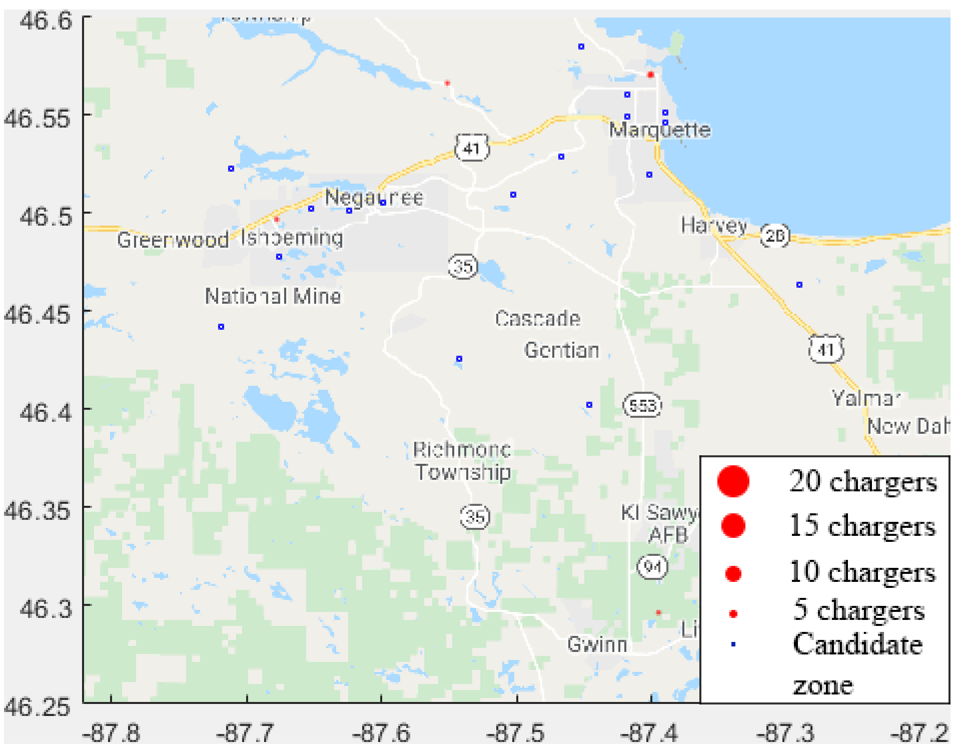


Figure 10. 100 kWh battery-150 kW charger configuration for city of Marquette

City of Muskegon

Table 7. Scenario results for the city of Muskegon: charging stations, chargers, required investment, and charge time

Scenario	1	2	3	4
Battery size (kWh)	70	100	70	100
Charging power (kW)	50	50	150	150
Number of zones	52	52	52	52
EV trips per day	12,729	12,729	12,729	12,729
Number of stations	9	9	8	6
Number of chargers	44	48	19	18
Station cost (Million dollar)	1.00	1.00	1.14	0.86
Charger cost (Million dollar)	1.57	1.72	1.49	1.41
Total infrastructure cost (Million dollar)	2.57	2.72	2.63	2.27
Average charging and queuing delay (min)	10.99	15.13	3.94	5.39

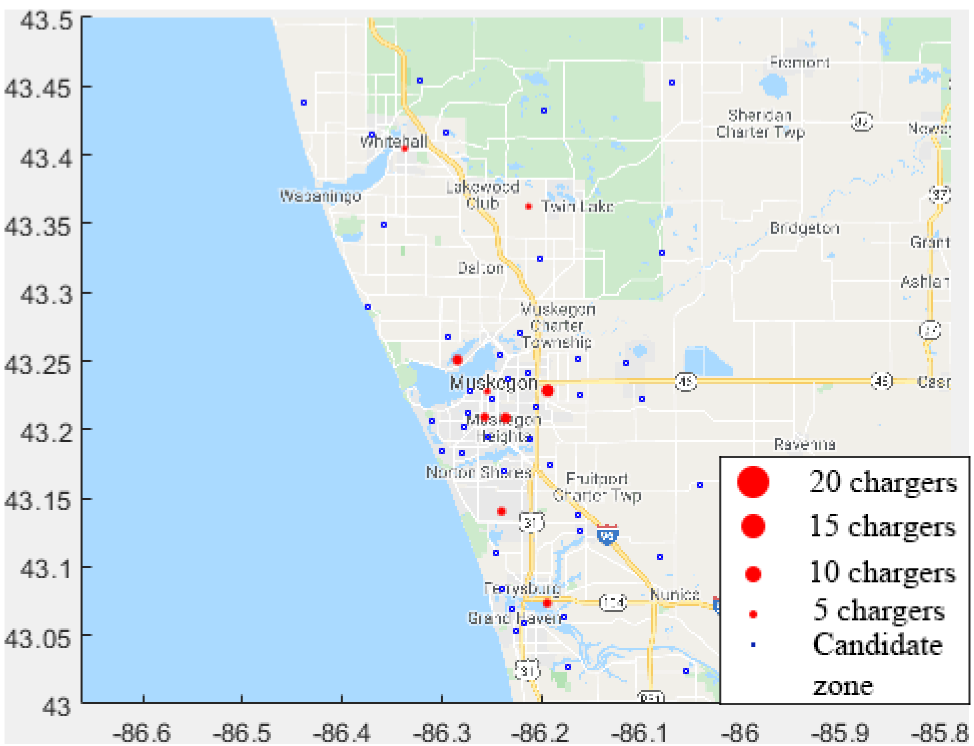


Figure 11. 70 kWh battery-50 kW charger configuration for the city of Muskegon

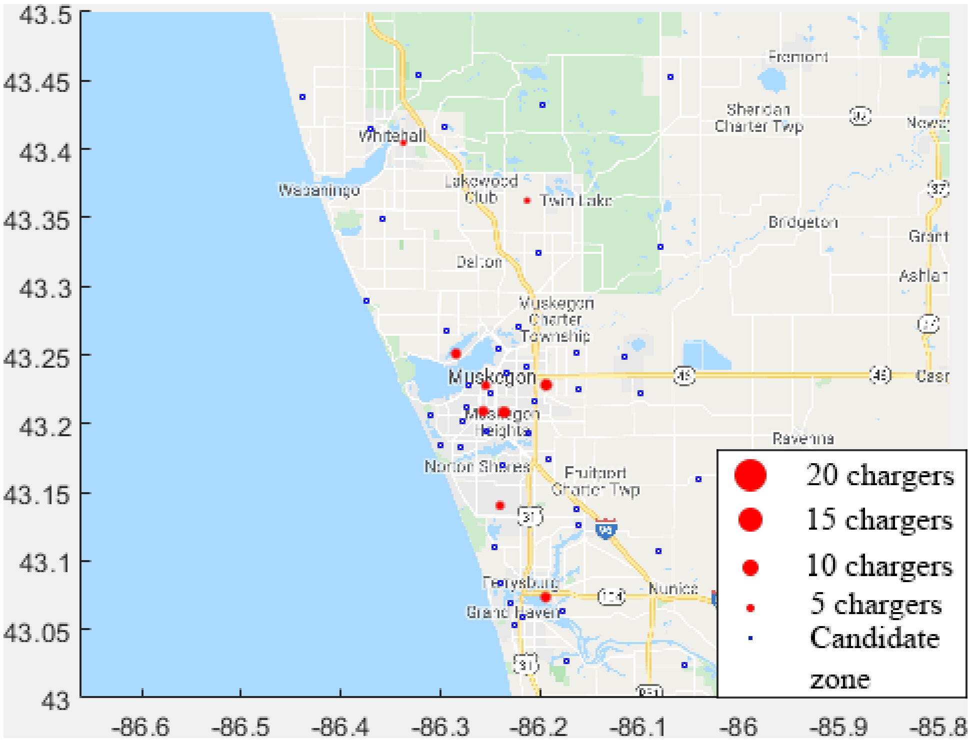


Figure 12. 100 kWh battery-50 kW charger configuration for the city of Muskegon

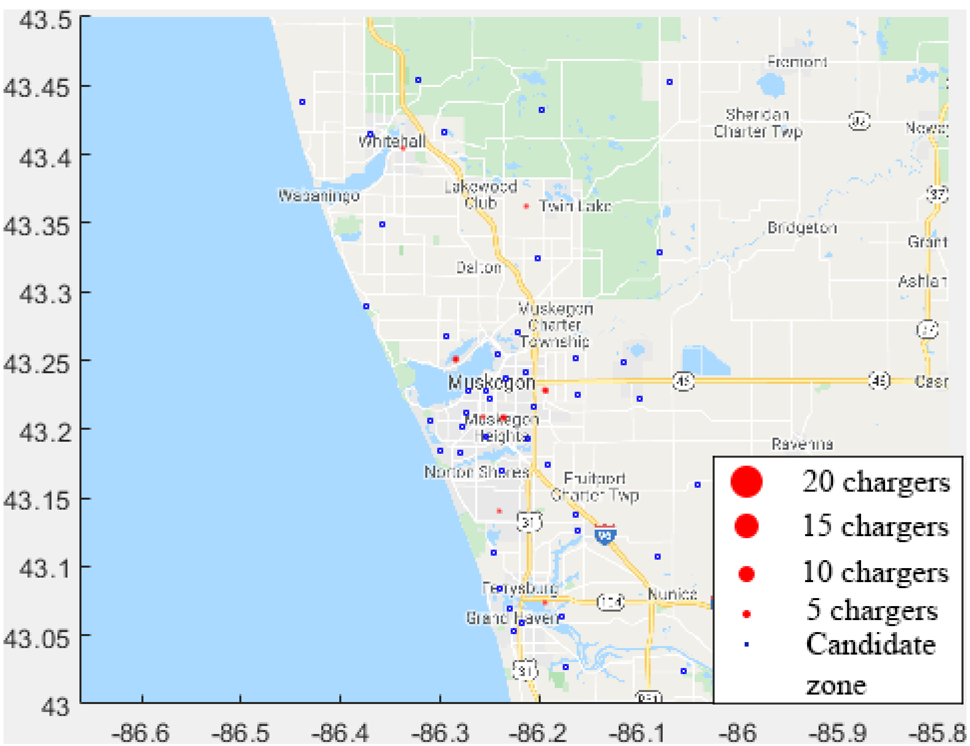


Figure 13. 70 kWh battery-150 kW charger configuration for the city of Muskegon

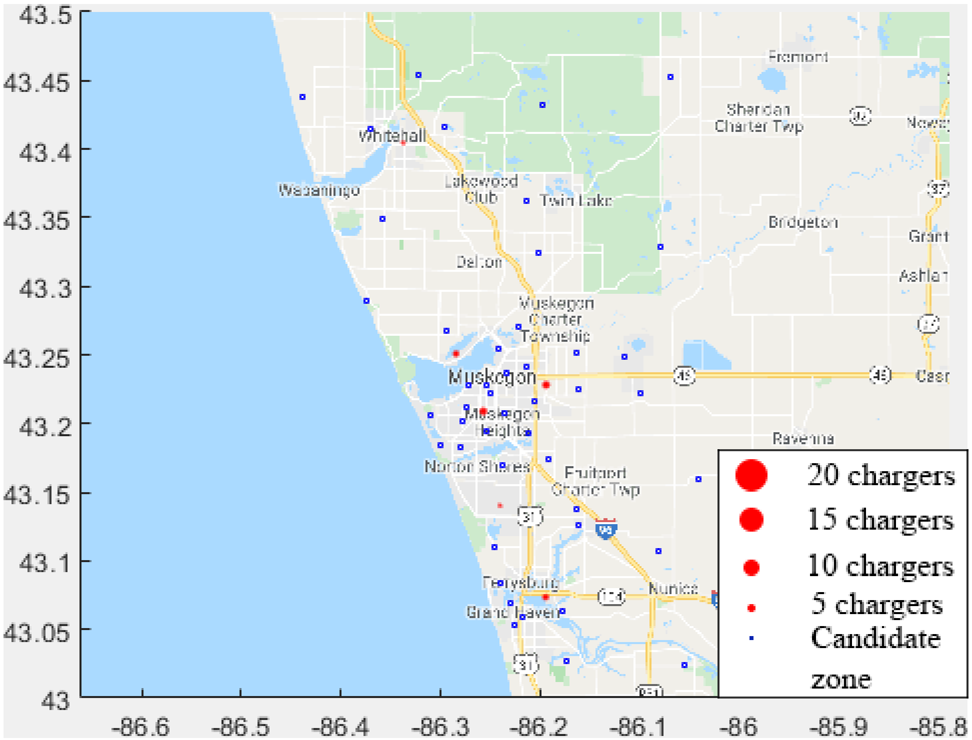


Figure 14. 100 kWh battery-150 kW charger configuration for the city of Muskegon

City of Ann Arbor

Table 8. Scenario results for the city of Ann Arbor: charging stations, chargers, required investment, and charge time

Scenario	1	2	3	4
Battery size (kWh)	70	100	70	100
Charging power (kW)	50	50	150	150
Number of zones	36	36	36	36
EV trips per day	11,530	11,530	11,530	11,530
Number of stations	3	3	3	3
Number of chargers	24	29	10	11
Station cost (Million dollar)	0.81	0.80	0.90	0.90
Charger cost (Million dollar)	1.00	1.22	0.84	0.92
Total infrastructure cost (Million dollar)	1.81	2.02	1.74	1.82
Average charging and queuing delay (min)	11.35	15.35	4.01	5.50

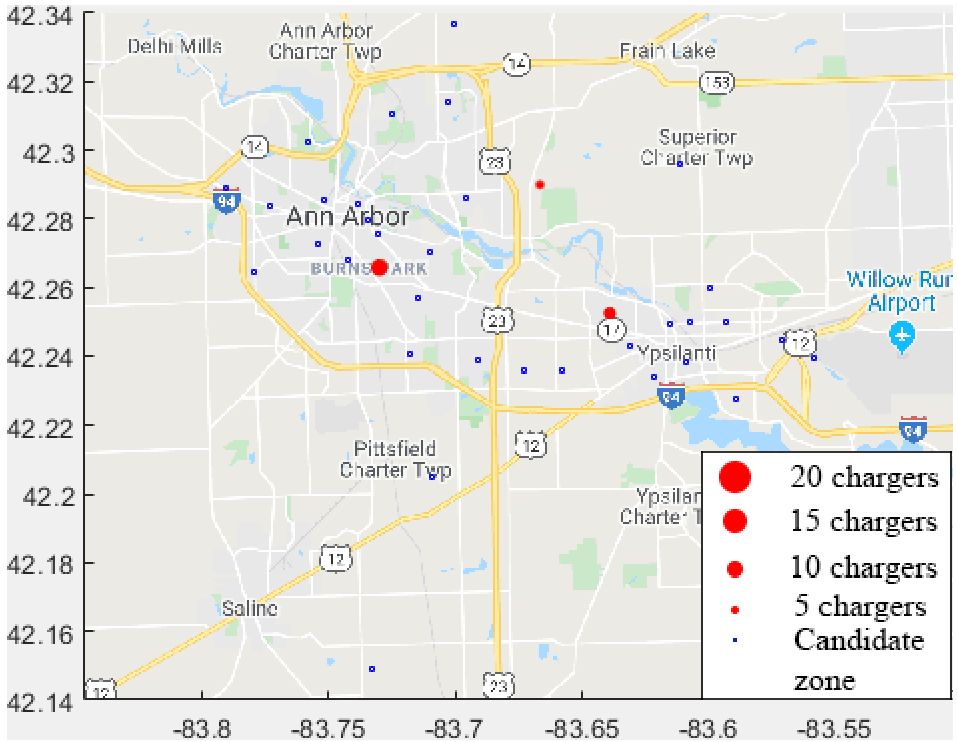


Figure 15. 70 kWh battery-50 kW charger configuration for the city of Ann Arbor

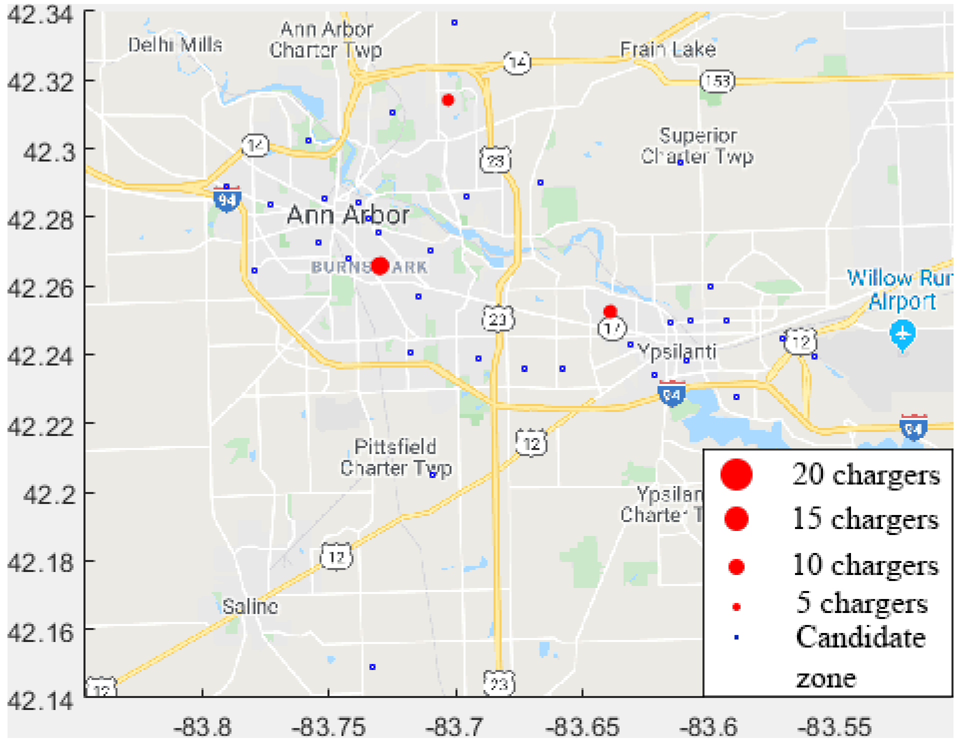


Figure 16. 100 kWh battery-50 kW charger configuration for the city of Ann Arbor

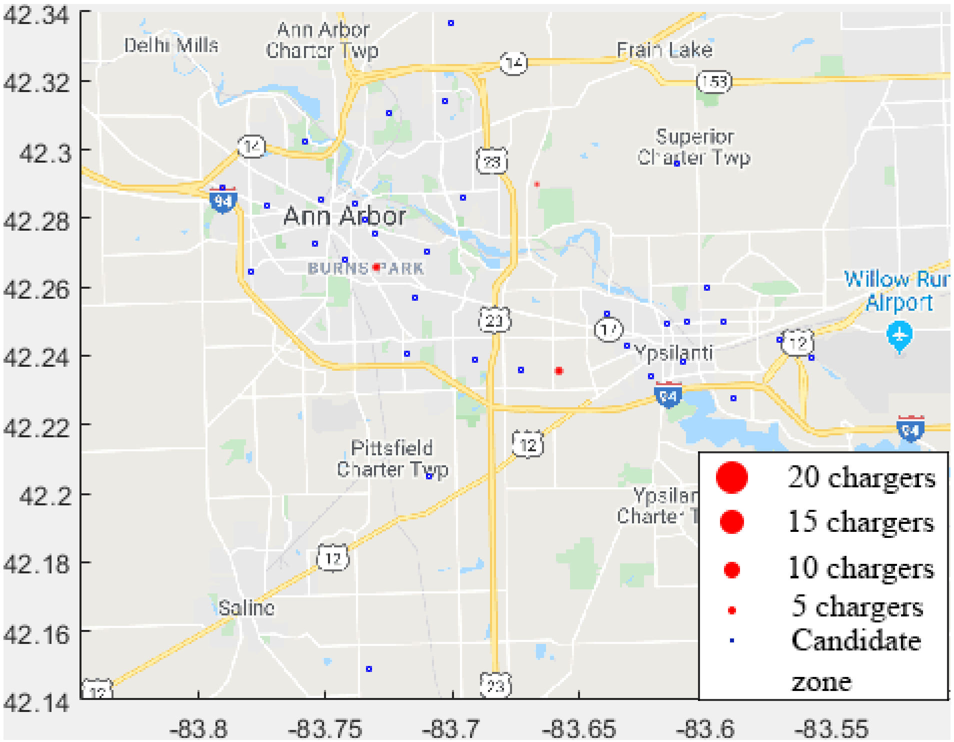


Figure 17. 70 kWh battery-150 kW charger configuration for the city of Ann Arbor

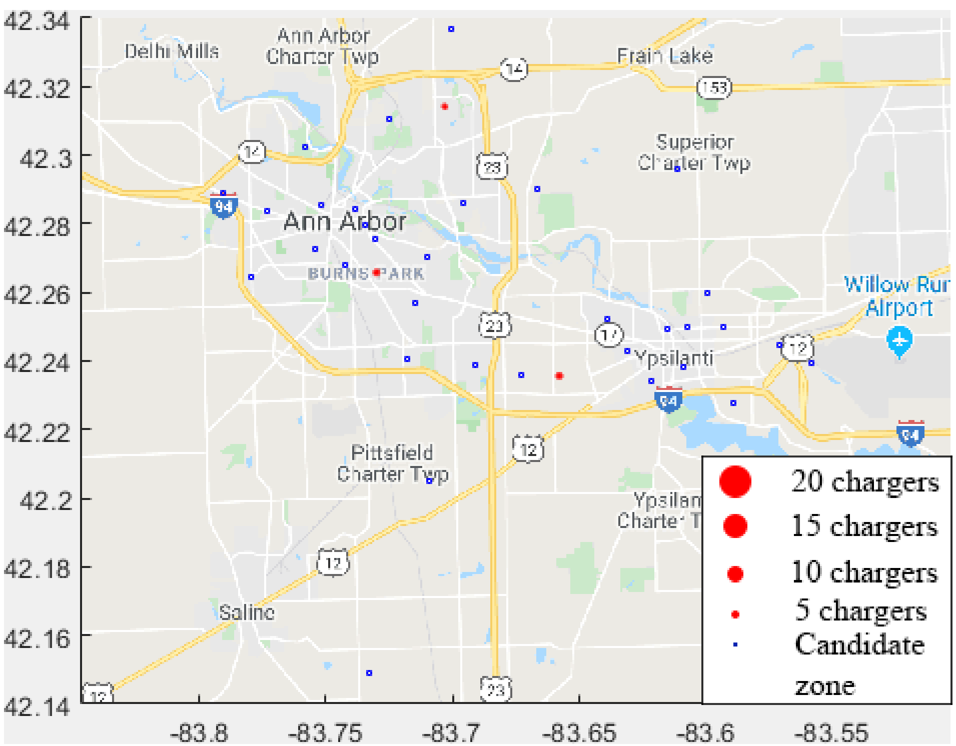


Figure 18. 100 kWh battery-150 kW charger configuration for the city of Ann Arbor

City of Kalamazoo

Table 9. Scenario results for the city of Kalamazoo: charging stations, chargers, required investment, and charge time

Scenario	1	2	3	4
Battery size (kWh)	70	100	70	100
Charging power (kW)	50	50	150	150
Number of zones	55	55	55	55
EV trips per day	16,460	16,460	16,460	16,460
Number of stations	12	11	8	7
Number of chargers	55	57	21	19
Station cost (Million dollar)	1.31	1.20	1.13	0.99
Charger cost (Million dollar)	1.95	2.02	1.64	1.48
Total infrastructure cost (Million dollar)	3.26	3.22	2.77	2.47
Average charging and queuing delay (min)	10.64	14.63	3.79	5.43

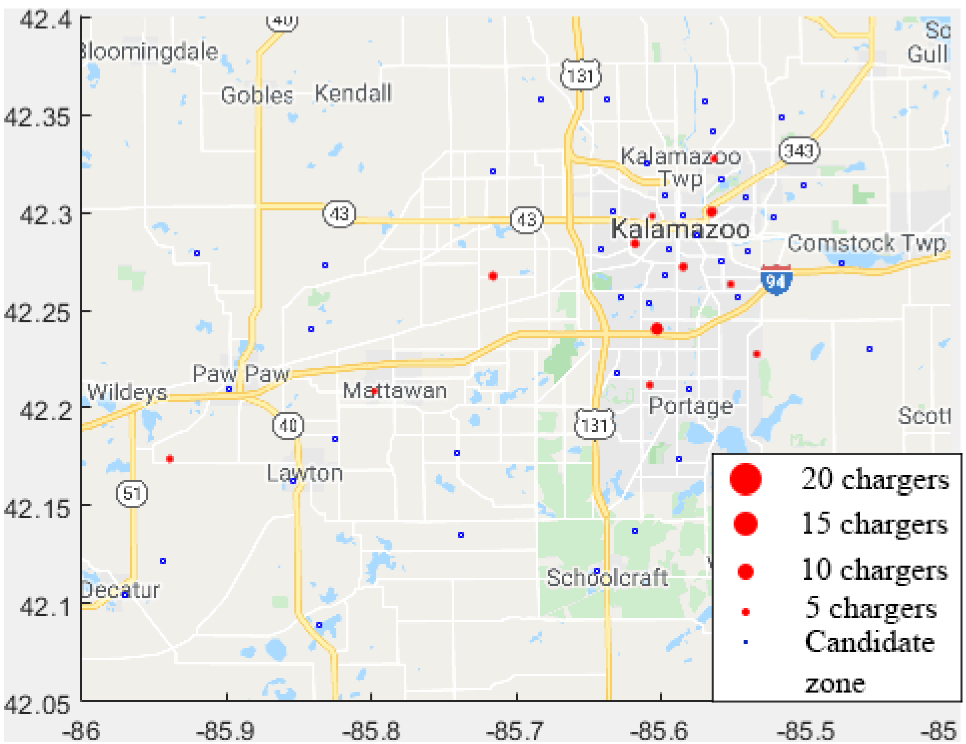


Figure 19. 70 kWh battery-50 kW charger configuration for the city of Kalamazoo

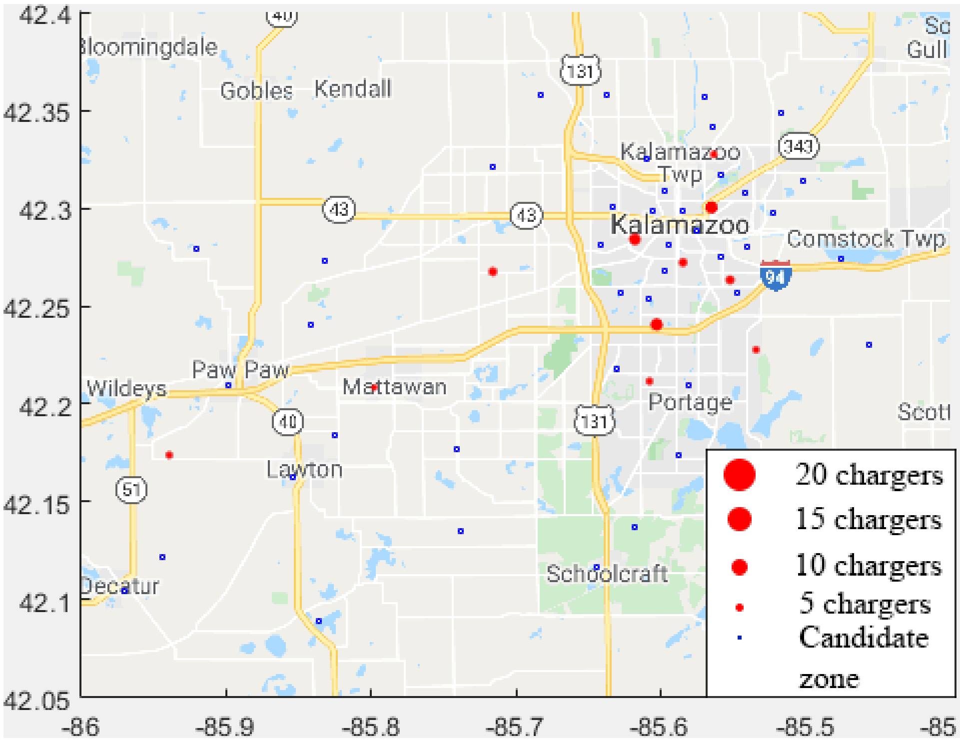


Figure 20. 100 kWh battery-50 kW charger configuration for the city of Kalamazoo

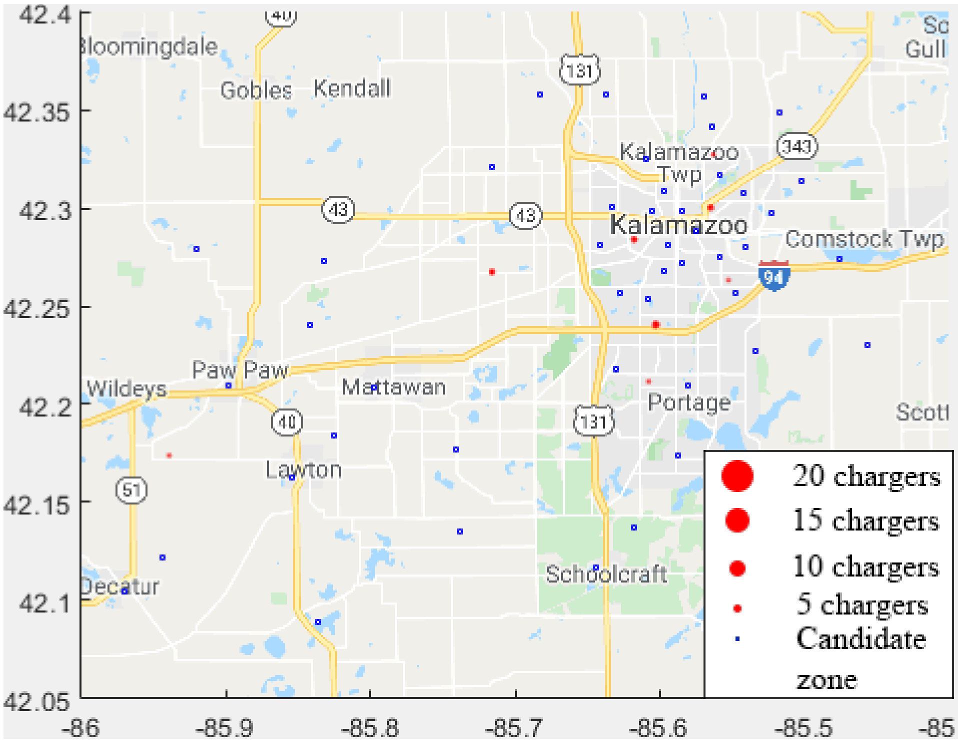


Figure 21. 70 kWh battery-150 kW charger configuration for the city of Kalamazoo

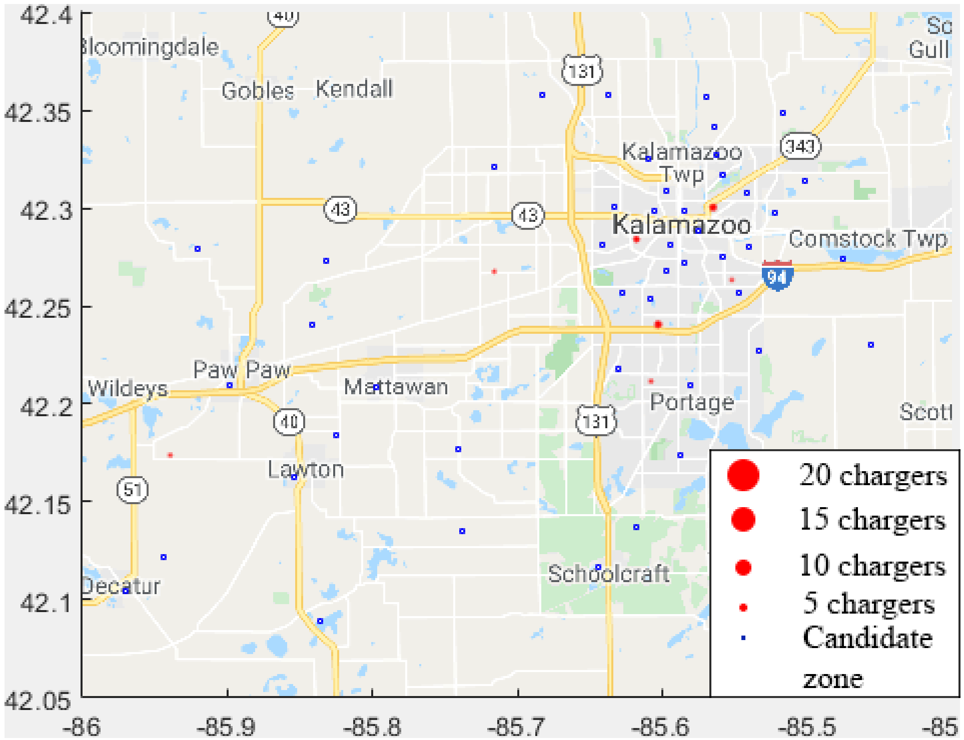


Figure 22. 100 kWh battery-150 kW charger configuration for the city of Kalamazoo

City of Flint

Table 10. Scenario results for the city of Flint: charging stations, chargers, required investment, and charge time

Scenario	1	2	3	4
Battery size (kWh)	70	100	70	100
Charging power (kW)	50	50	150	150
Number of zones	84	84	84	84
EV trips per day	22,133	22,133	22,133	22,133
Number of stations	14	12	12	8
Number of chargers	71	73	31	26
Station cost (Million dollar)	2.06	1.76	2.14	1.43
Charger cost (Million dollar)	2.56	2.63	2.43	2.04
Total infrastructure cost (Million dollar)	4.62	4.39	4.58	3.47
Average charging and queuing delay (min)	10.97	14.90	3.85	5.32

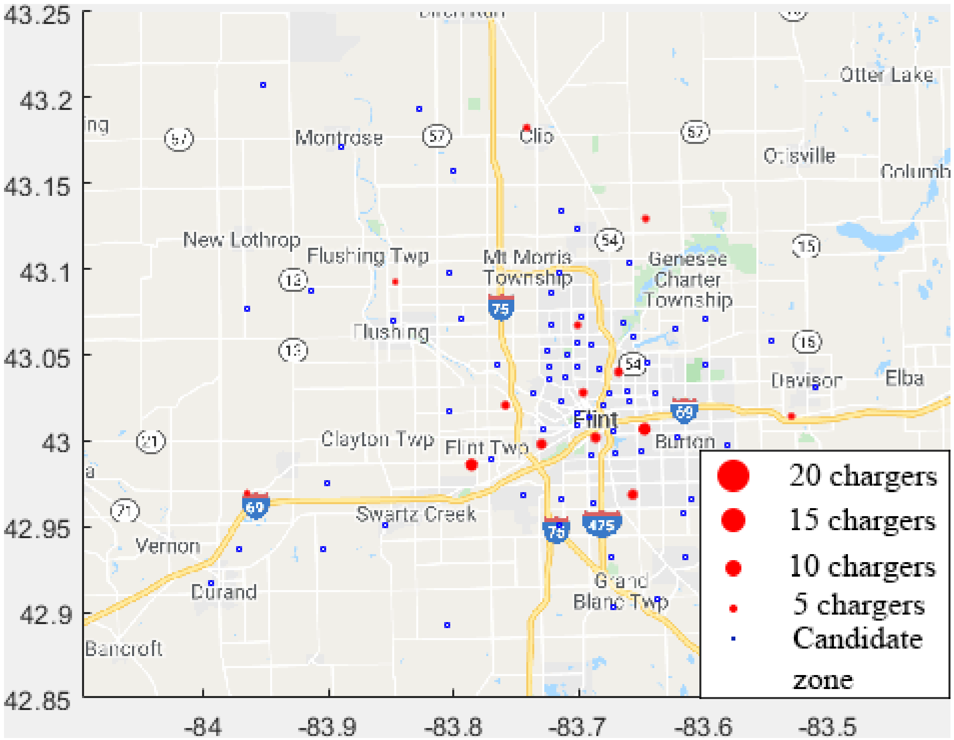


Figure 23. 70 kWh battery-50 kW charger configuration for the city of Flint

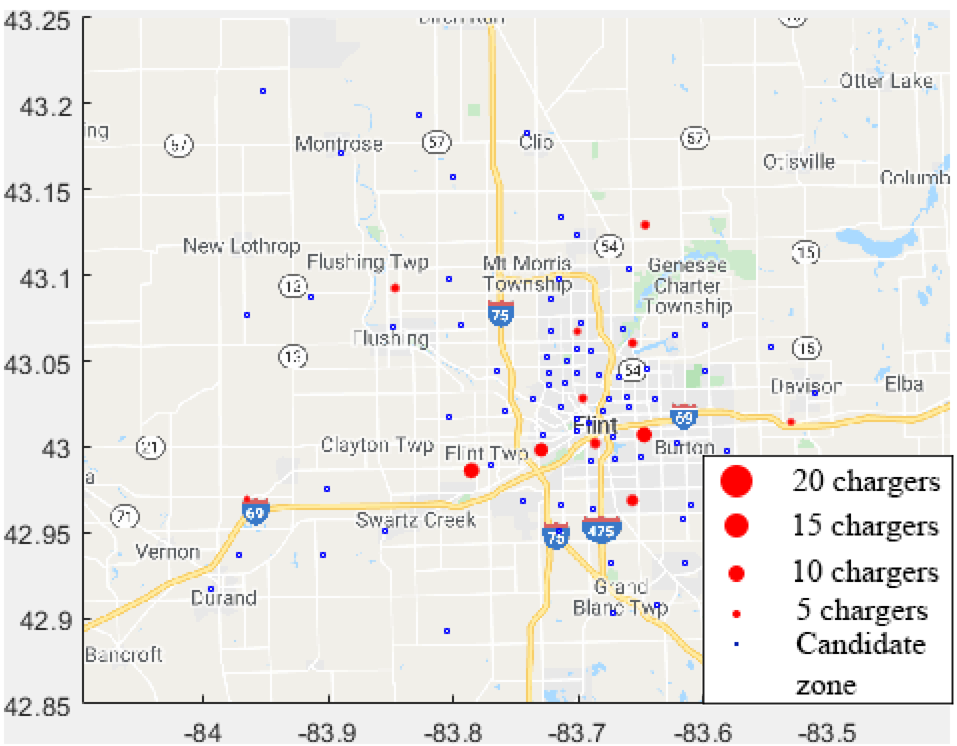


Figure 24. 100 kWh battery-50 kW charger configuration for the city of Flint

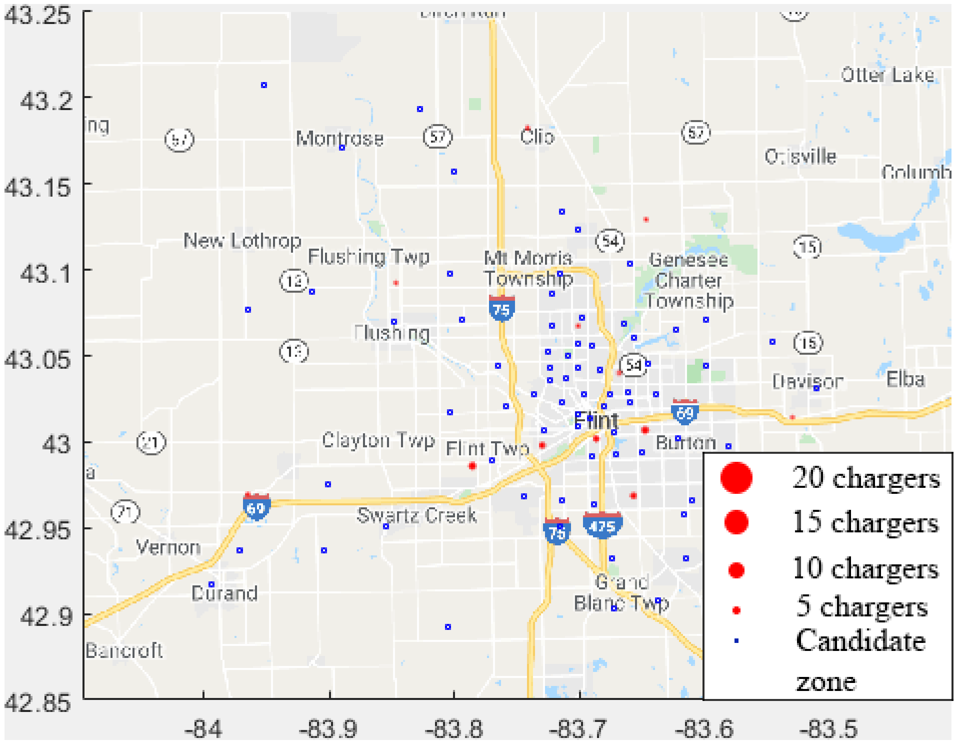


Figure 25. 70 kWh battery-150 kW charger configuration for the city of Flint

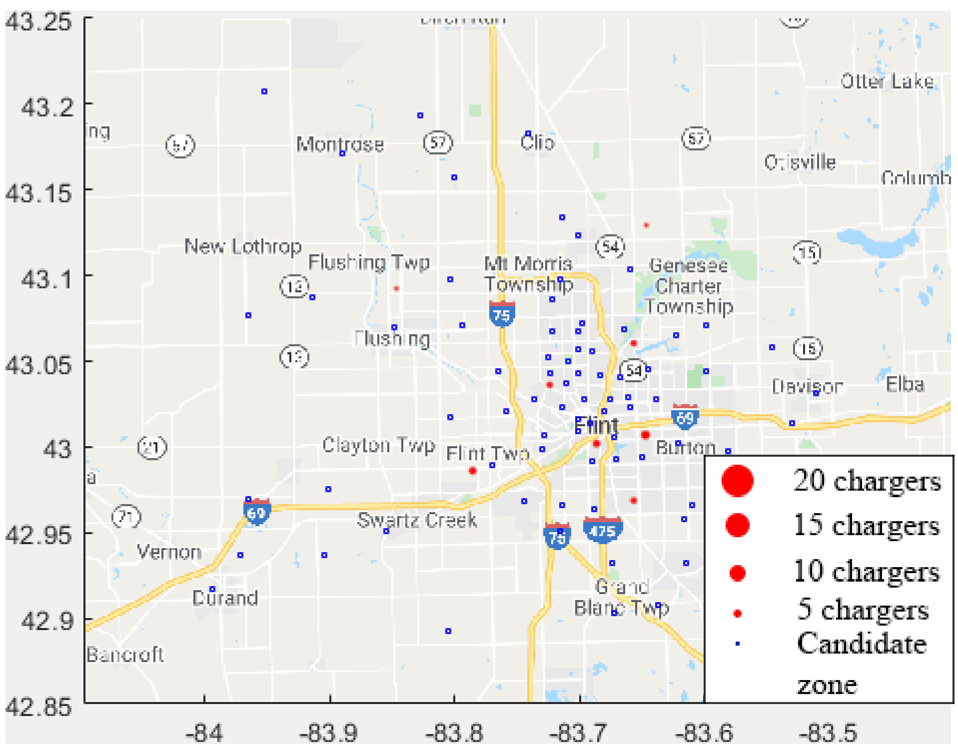


Figure 26. 100 kWh battery-150 kW charger configuration for the city of Flint

City of Saginaw

Table 11. Scenario results for the city of Saginaw: charging stations, chargers, required investment, and charge time

Scenario	1	2	3	4
Battery size (kWh)	70	100	70	100
Charging power (kW)	50	50	150	150
Number of zones	116	116	116	116
EV trips per day	26,076	26,076	26,076	26,076
Number of stations	27	23	23	17
Number of chargers	123	122	54	45
Station cost (Million dollar)	2.60	2.21	2.94	2.17
Charger cost (Million dollar)	4.40	4.36	4.23	3.52
Total infrastructure cost (Million dollar)	7.00	6.58	7.17	5.70
Average charging and queuing delay (min)	11.64	15.82	4.11	5.68

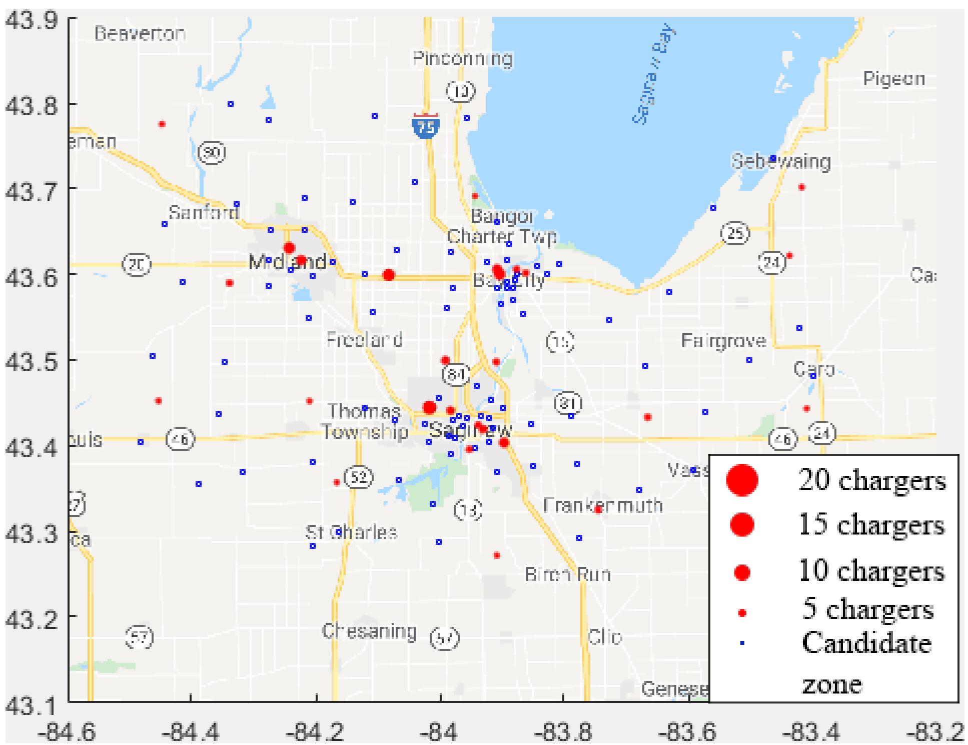


Figure 27. 70 kWh battery-50 kW charger configuration for the city of Saginaw

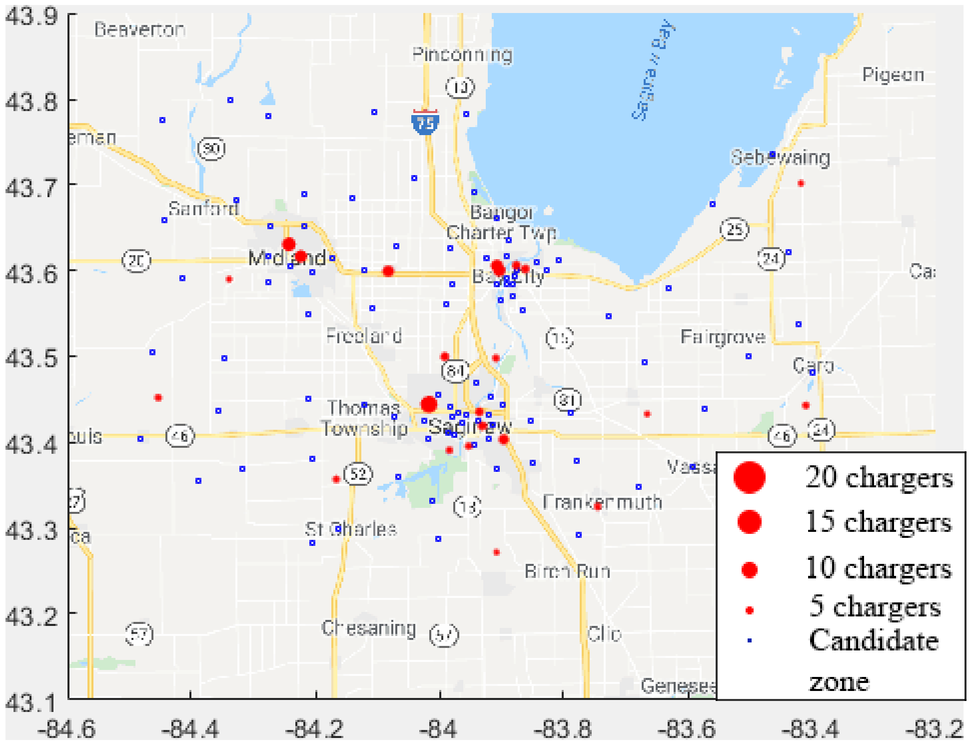


Figure 28. 100 kWh battery-50 kW charger configuration for the city of Saginaw

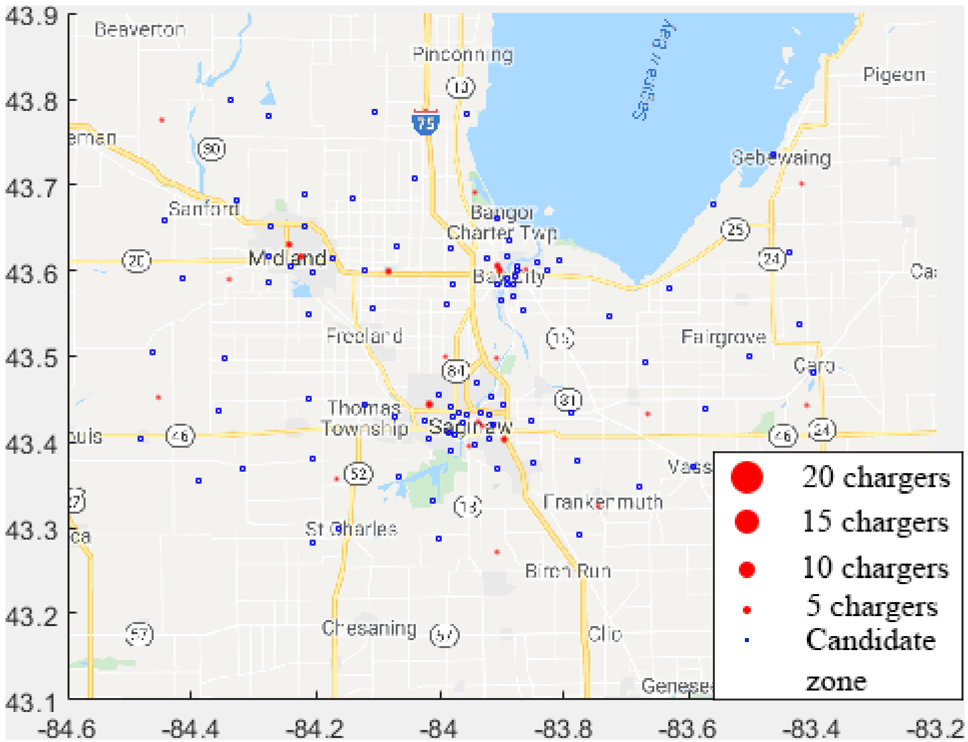


Figure 29. 70 kWh battery-150 kW charger configuration for the city of Saginaw

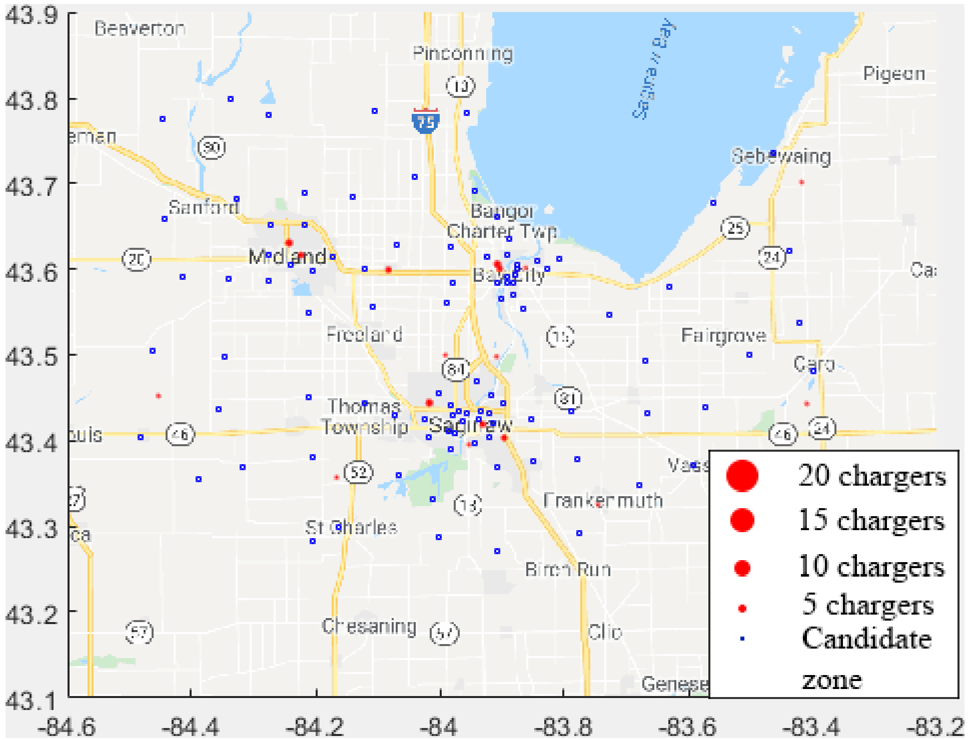


Figure 30. 100 kWh battery-150 kW charger configuration for the city of Saginaw

City of Lansing

Table 12. Scenario results for the city of Lansing: charging stations, chargers, required investment, and charge time

Scenario	1	2	3	4
Battery size (kWh)	70	100	70	100
Charging power (kW)	50	50	150	150
Number of zones	92	92	92	92
EV trips per day	28,574	28,574	28,574	28,574
Number of stations	16	14	13	10
Number of chargers	85	89	36	33
Station cost (Million dollar)	2.52	2.21	2.47	1.88
Charger cost (Million dollar)	3.39	3.56	2.96	2.73
Total infrastructure cost (Million dollar)	5.91	5.78	5.43	4.62
Average charging and queuing delay (min)	10.80	14.74	3.83	5.26

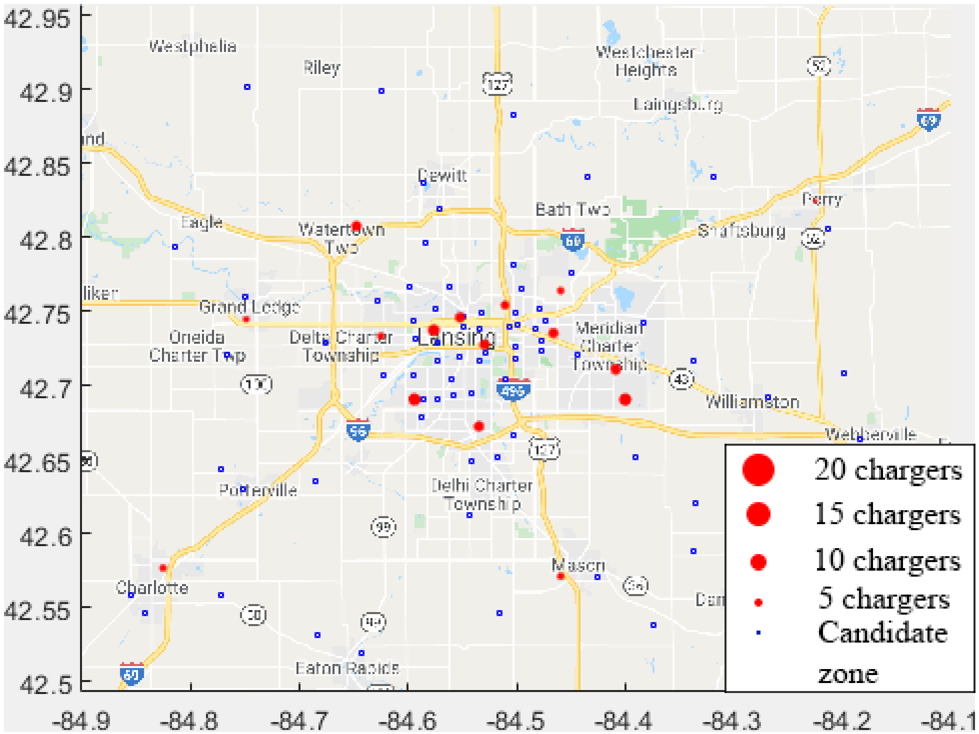


Figure 31. 70 kWh battery-50 kW charger configuration for the city of Lansing

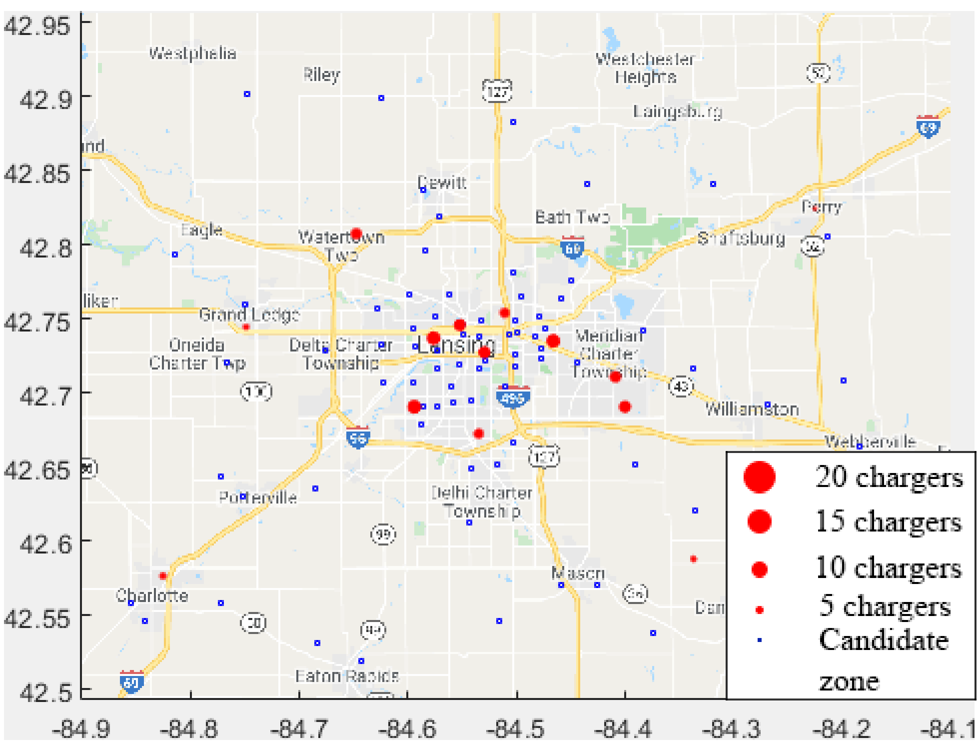


Figure 32. 100 kWh battery-50 kW charger configuration for the city of Lansing

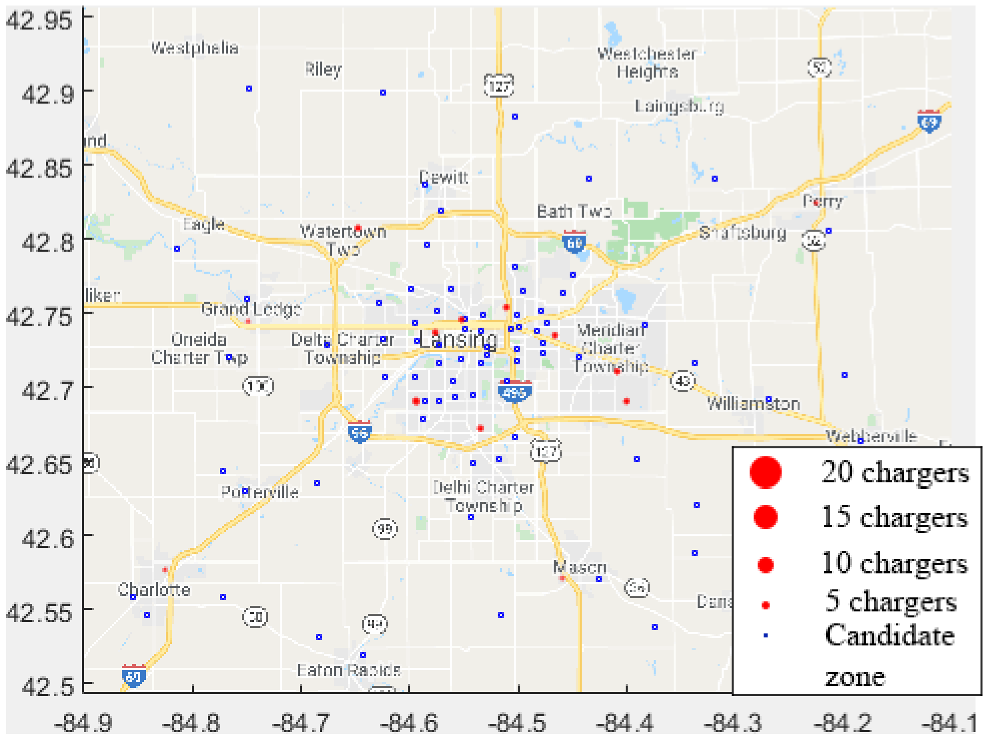


Figure 33. 70 kWh battery-150 kW charger configuration for the city of Lansing

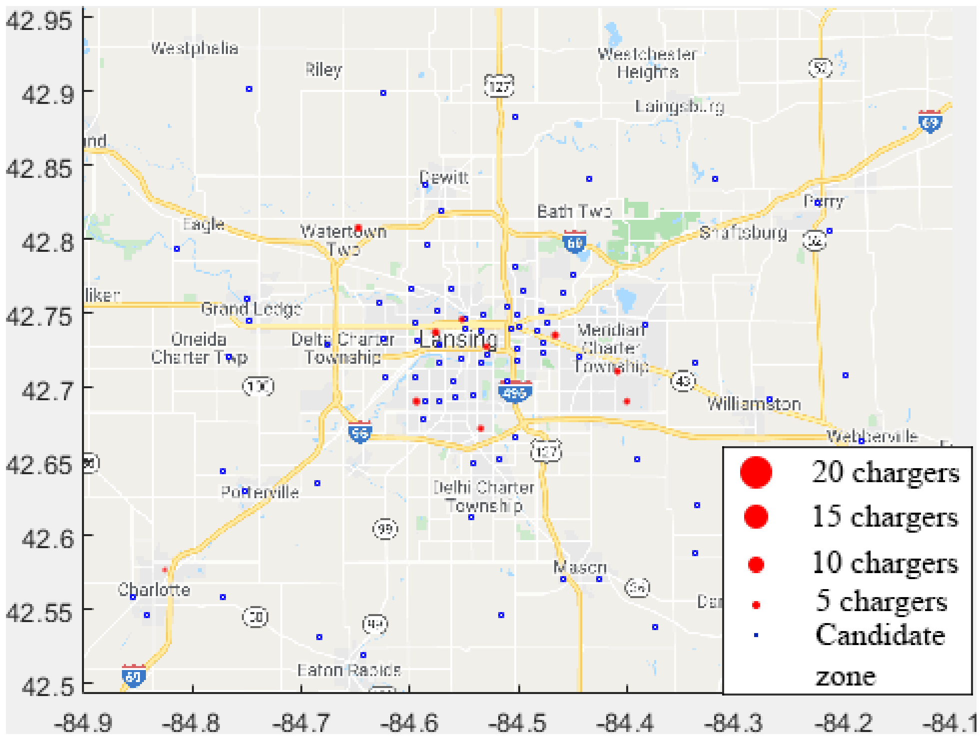


Figure 34. 100 kWh battery-150 kW charger configuration for the city of Lansing

City of Grand Rapids

Table 13. Scenario results for the city of Grand Rapids: charging stations, chargers, required investment, and charge time

Scenario	1	2	3	4
Battery size (kWh)	70	100	70	100
Charging power (kW)	50	50	150	150
Number of zones	82	82	82	82
EV trips per day	42,383	42,383	42,383	42,383
Number of stations	17	16	14	12
Number of chargers	122	132	47	48
Station cost (Million dollar)	2.79	2.63	2.74	2.35
Charger cost (Million dollar)	4.33	4.68	3.66	3.74
Total infrastructure cost (Million dollar)	7.12	7.31	6.41	6.09
Average charging and queuing delay (min)	10.53	14.65	3.79	5.20

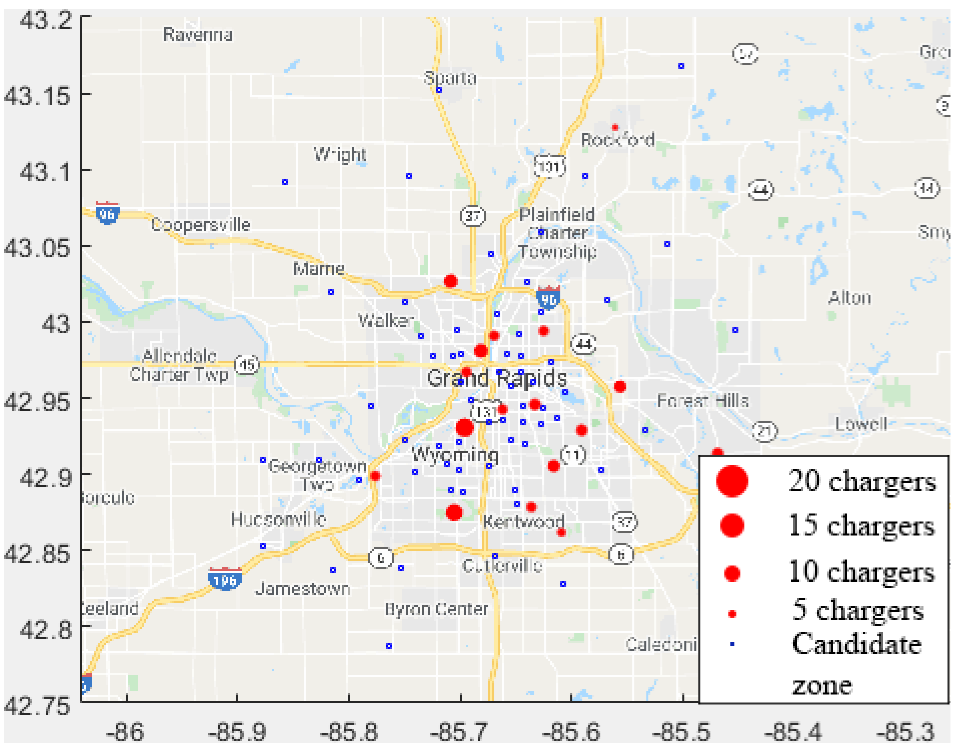


Figure 35. 70 kWh battery-50 kW charger configuration for the city of Grand Rapids

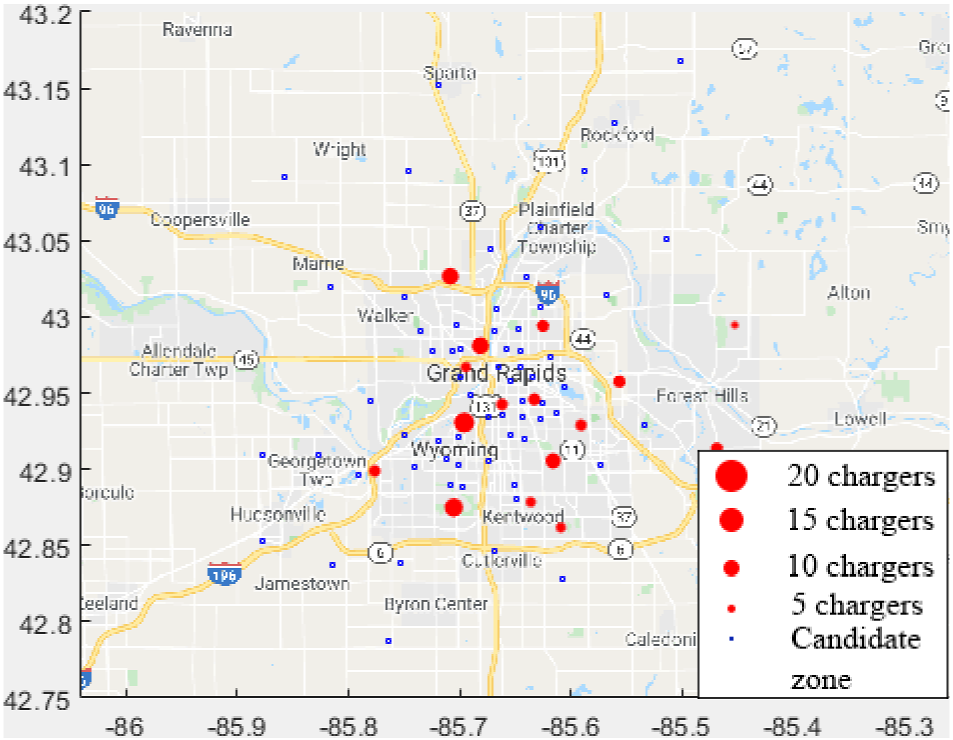


Figure 36. 100 kWh battery-50 kW charger configuration for the city of Grand Rapids

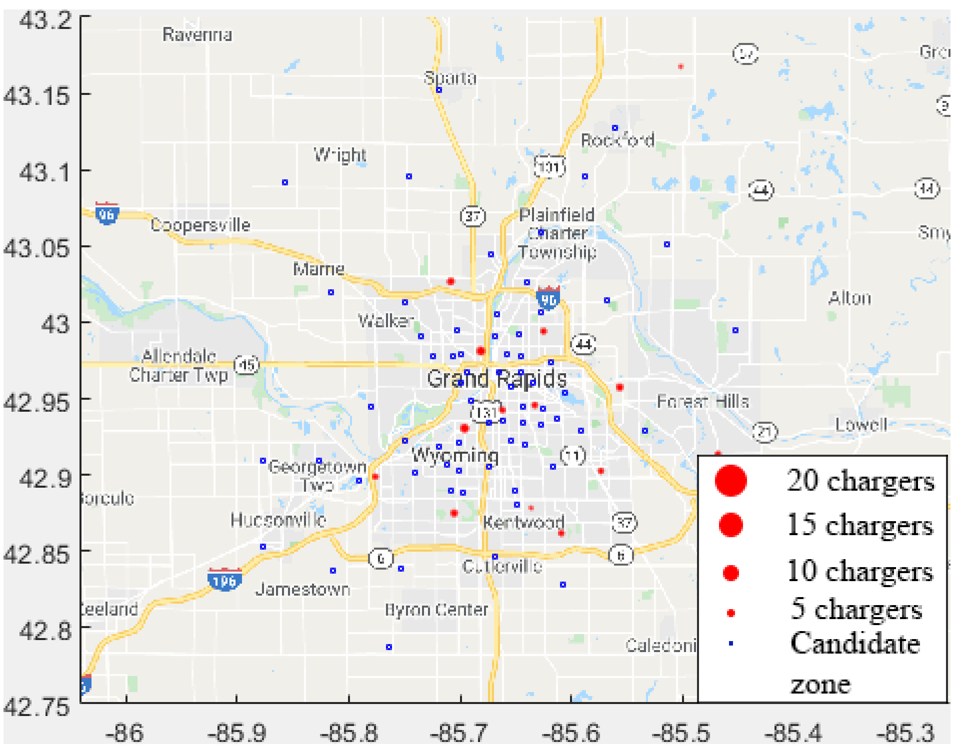


Figure 37. 70 kWh battery-150 kW charger configuration for the city of Grand Rapids

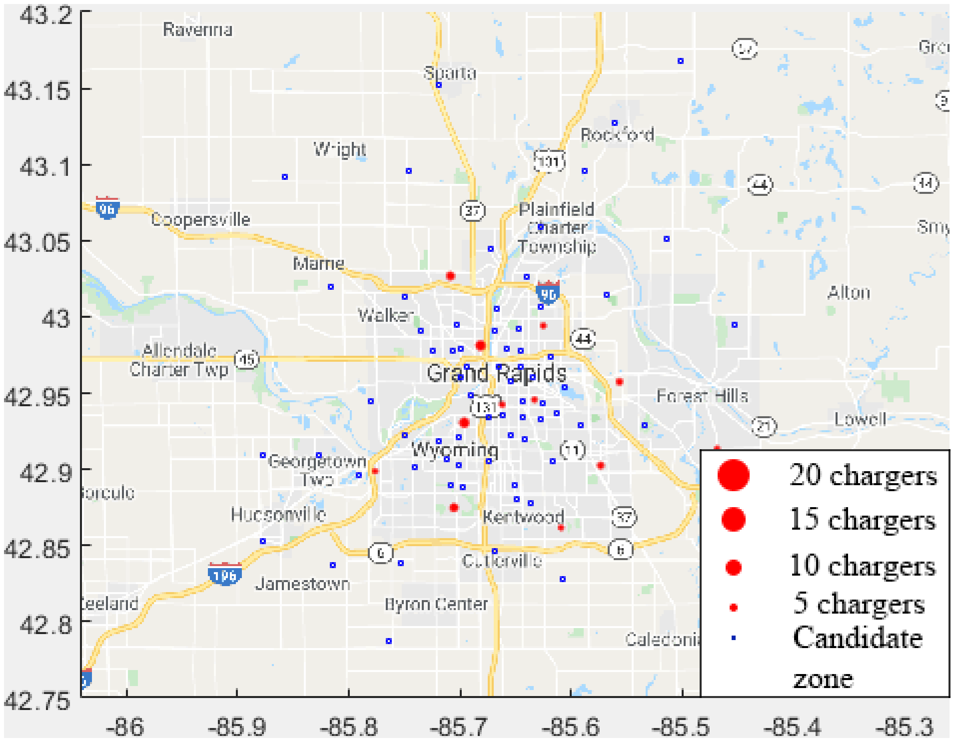


Figure 38. 100 kWh battery-150 kW charger configuration for the city of Grand Rapids

City of Detroit

Table 14. Scenario results for the city of Detroit: charging stations, chargers, required investment, and charge time

Scenario	1	2	3	4
Battery size (kWh)	70	100	70	100
Charging power (kW)	50	50	150	150
Number of zones	301	301	301	301
EV trips per day	212,299	212,299	212,299	212,299
Number of stations	62	50	47	42
Number of chargers	636	626	236	233
Station cost (Million dollar)	15.37	12.39	13.14	11.74
Charger cost (Million dollar)	23.04	22.68	18.58	18.34
Total infrastructure cost (Million dollar)	38.41	35.07	31.72	30.09
Average charging and queuing delay (min)	11.49	15.40	3.97	5.30

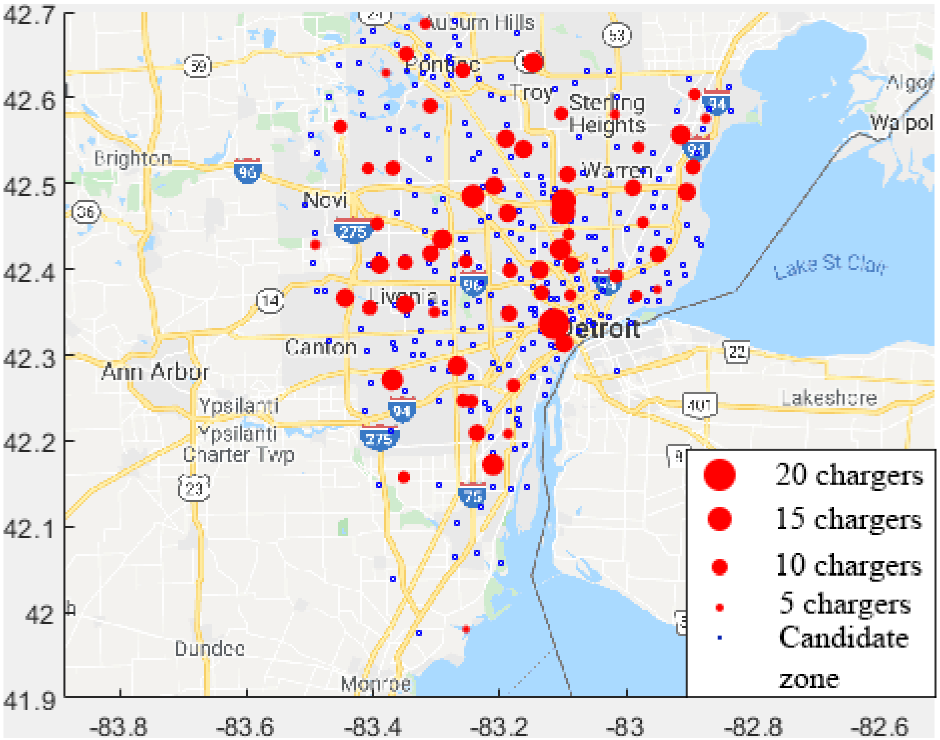


Figure 39. 70 kWh battery-50 kW charger configuration for the city of Detroit

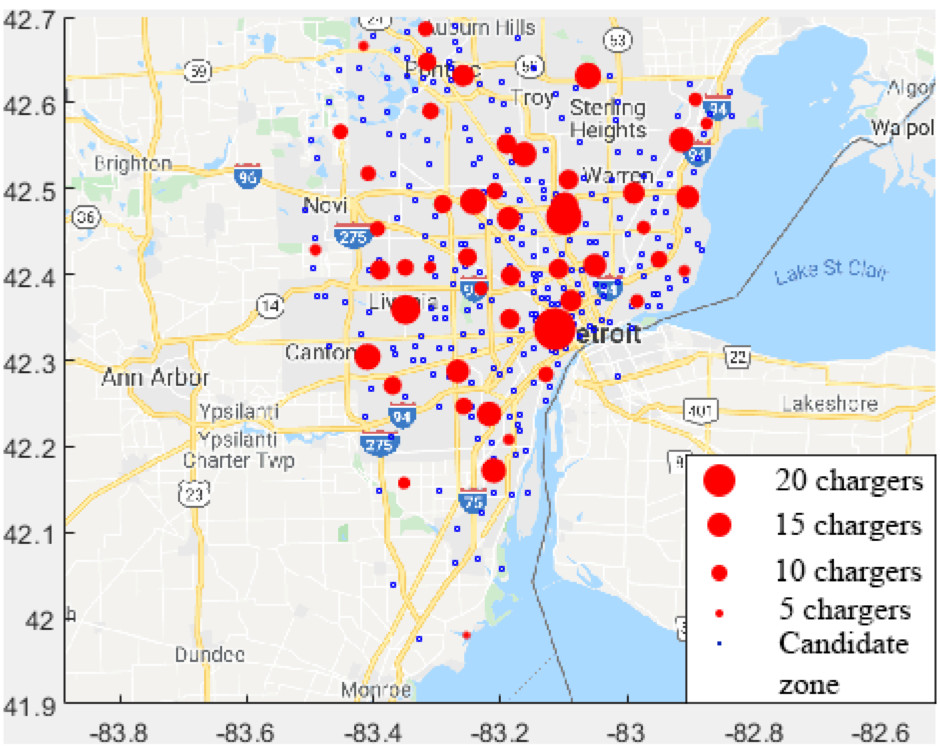


Figure 40. 100 kWh battery-50 kW charger configuration for the city of Detroit

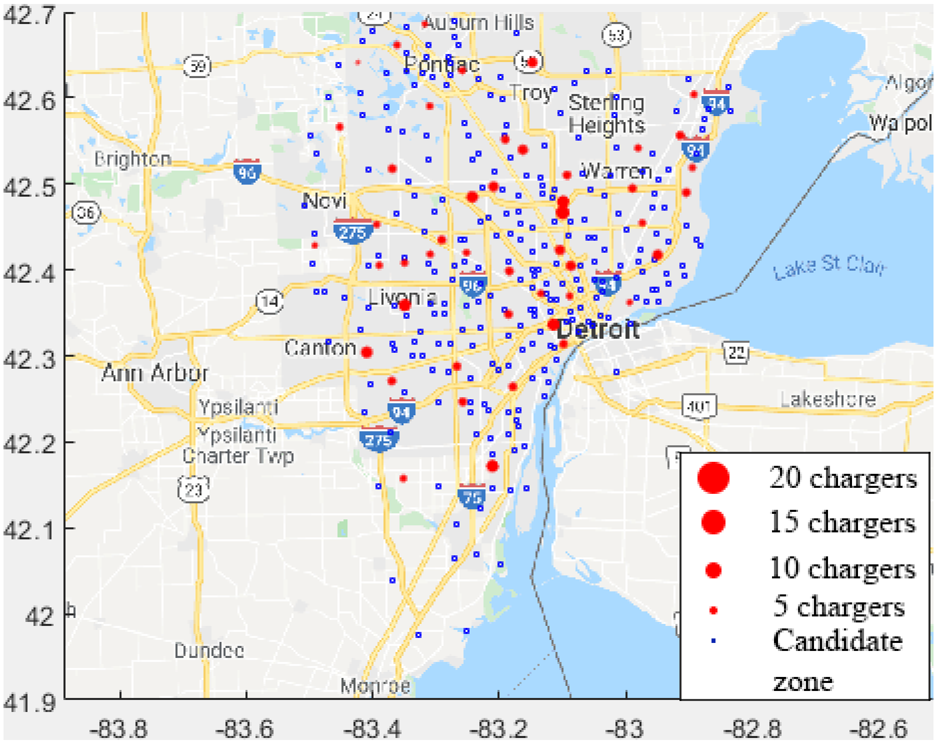


Figure 41. 70 kWh battery-150 kW charger configuration for the city of Detroit

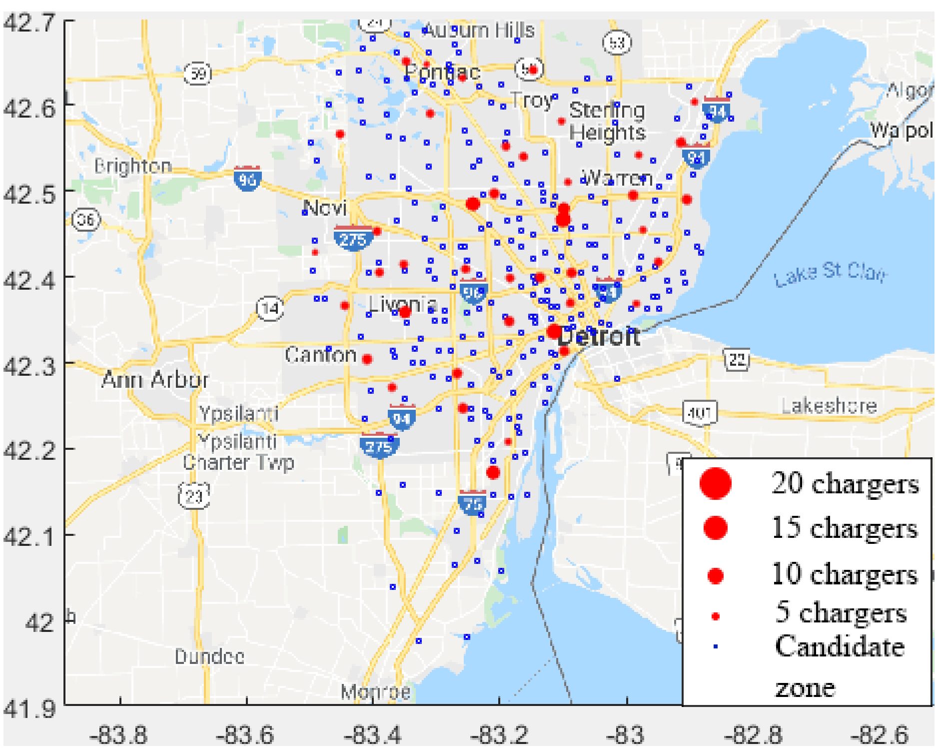


Figure 42. 100 kWh battery-150 kW charger configuration for the city of Detroit

Regression Models and Results for Charging Station and Charger Counts for Smaller Urban Areas

The specifications of the eight major urban areas and their optimal charging configurations, which are shown in Table. 15, are used to develop regression models. These urban areas are Muskegon, Ann Arbor, Flint, Saginaw, Grand Rapids, Kalamazoo, Lansing, and Detroit. Marquette was excluded due to its smaller size relative to the other cities. The inputs considered to estimate the regression models include the number of traffic analysis zones, the number of generated trips, total roadway length (lane miles), and VMT. The regression models are estimated using the input data from MDOT and the optimum charging configuration of Muskegon, Ann Arbor, Flint, Saginaw, Grand Rapids, and Detroit based on the optimization model results for these cities. Then, the regression models are validated using the data points available for Kalamazoo and Lansing. To this end, the predicted values of the regression models are compared with the optimum values obtained from the optimization model for these cities. The regression models were estimated for the scenario with 70 kWh battery size and 150 kW charging power.

Table 15. The regression models dataset

Cities	Independent Variables				Dependent Variables	
	Number of Traffic Analysis Zones	Number of Generated Trips	Total Roadway Length (Lane Miles)	Daily Vehicle Miles Traveled	Number of Charging Stations	Number of Chargers
Muskegon	52	535,443	916	3,161,057	8	19
Ann Arbor	36	624,618	789	3,894,950	3	10
Kalamazoo	55	712,796	1128	4,085,052	8	21
Flint	84	985,411	1557	6,760,436	12	31
Saginaw	116	1,054,842	2726	7,122,931	23	54
Lansing	91	1,086,242	2030	7,183,037	13	36
Grand Rapids	82	1,726,732	2045	10,447,668	14	47
Detroit	301	8,185,778	8776	52,293,864	47	236

Some variables are scaled down to obtain meaningful coefficient values in the regression model, e.g. the number of generated trips (million trips), total roadway length (thousand miles), and VMT (million miles).

Considering the above-mentioned factors, the best regression models for the total number of charging stations and chargers are presented in Equation 7 and Equation 8, respectively. These models have the best values for adjusted R squared and RMSE, presented in Table 16 and Table 17. All the independent variables are statistically significant (p-value). Further, the comparison of the number of charging stations and the chargers, estimated by the regression model to that of the optimization model, is presented in Table 18.

$$Number\ of\ charging\ stations = 3.4 + 0.8\left[Total\ Roadway\ Length \times \left(\frac{VMT}{Generated\ Trips}\right)\right] \quad (7)$$

$$Number\ of\ chargers = max[2(Number\ of\ charging\ stations), -7.7 + 9.0(Number\ of\ Generated\ Trips) + 19.4(Total\ Roadway\ Length\ )] \quad (8)$$

Table 16. Regression model characteristics for the number of charging stations

Variables	Coefficients	p-value	significance	R^2	$R^2_{adjusted}$	RMSE	RMSE validated*
Intercept	3.4	0.154	0.000	0.964	0.955	2.729	0.940
$Total\ Roadway\ Length \times \left(\frac{VMT}{Generated\ Trips}\right)$	0.8	0.000					

RMSE validated: *This term is similar to RMSE except that it is estimated for the urban areas used for validating the model (Lansing and Kalamazoo, in our case).*

Table 17. Regression model characteristics for the number of chargers

Variables	Coefficients	p-value	significance	R^2	$R^2_{adjusted}$	RMSE	RMSE validated*
Intercept	-7.7	0.041	0.000	0.999	0.999	2.161	3.789
Number of Generated Trips	9.0	0.039					
Total Roadway Length	19.4	0.005					

RMSE validated: *This term is similar to RMSE except that it is estimated for the urban areas used for validating the model (Lansing and Kalamazoo, in our case).*

Table 18. Estimated values from the optimization model and the regression model

Cities/Parameter	Number of stations (Optimization Model)	Number of stations (Regression Model)	Number of spots (Optimization Model)	Number of spots (Regression Model)
Muskegon	8	8	19	16
Ann Arbor	3	8	10	16
Kalamazoo	8	9	21	21
Flint	12	12	31	32
Saginaw	23	19	54	55
Lansing	13	15	36	42
Grand Rapids	14	14	47	48
Detroit	47	49	236	236

It can be observed that the number of stations is a function of the total roadway length and VMT per generated trip. A larger total roadway length represents a larger urban area. Hence, to make every trip feasible and to have less detours, the number of required charging stations increases with an increase in the length of the road network. Furthermore, as the average trip length (VMT per generated trip) increases, the vehicles are more likely to require charging during their trips. Hence, more charging stations are required within the city. The total number of chargers required in an urban area is a function of the length of the road network, and the demand generated (Table 16). With a larger total roadway length, the battery energy usage of vehicles increases, thereby, increasing the need for chargers. In addition, as each charging station should have at least two chargers, for redundancy and maintenance purposes, increasing the number of charging stations due to an increase in the total roadway length, increases the number of chargers required in the city. More number of generated trips result into an increased demand per charging station, hence, the number of required chargers increases to avoid long queuing delays.

Predicting the number of charging stations/chargers for the small cities in Michigan

The regression models presentred in Equation 7 and Equation 8 were used to estimate the number of charging stations and chargers for smaller urban areas in the state of Michigan. The list of these cities, the required input data, and the estimated number of charging stations and chargers are presented in Table 19.

Table 19. Number of charging stations and chargers for small urban areas of Michigan based on the results of the regression models

Cities	Inputs			Outputs	
	Number of Generated Trips	Total Roadway Length (Lane Miles)	Daily Vehicle Miles Traveled	Estimated Number of Charging Stations	Estimated Number of Chargers
Menominee	41,297	54	166,799	4	8
Sault Ste. Marie	61,412	133	229,042	4	8
Escanaba	103,491	260	479,245	5	10
Houghton	113,403	626	558,063	6	12
Traverse City	226,264	212	1,124,123	5	10
Battle Creek	245,167	406	1,385,189	6	12
Jackson	274,350	461	1,542,840	6	12
Port Huron	296,516	918	2,717,248	11	22
Holland	373,233	525	2,279,219	6	12

CONCLUSION

This study developed a methodological framework to find the optimum investment plan for building a network of charging stations for different urban areas in the state of Michigan. This report presents the research approach and results for different urban areas in Michigan to ensure the feasibility of the urban trips of EV users in the state by 2030. Major urban areas usually have more resources to gather travel and road network data, while this type of information is usually very limited in smaller urban areas. Depending on the availability of data, the results for major urban areas in Michigan are provided based on the optimization-based approach and hence presented in more details, while the results for smaller urban areas are based on the regression models and presented in a more aggregate form. The results of this report can be used by local governments to plan their investments on building EV charging infrastructures within their communities. This study suggests a list of locations for charging stations and the number of chargers at each location, with an approximate cost of building such network for major urban areas in the state. The tables and figures of these results are available in the results section, as well as the appendices. For smaller urban areas in Michigan the minimum number of chargers and charging stations is suggested in this report for each urban area. During the series of stakeholder meetings, different scenarios with different vehicles and charger technologies were suggested and tested for this study. The winter scenario with 70 percent battery performance is selected and battery energy levels of 70 kWh and 100 kWh, and charger power levels of 50 kW and 150 kW are tested.

The tested scenarios revealed the following findings:

- The 150 kW chargers reduce the charging and waiting time, compared to that of the 50kW chargers.
- Due to the higher throughput of 150kW charger, the number of 150 kW chargers needed to support the trips of EV users in urban areas is less than that of the 50 kW chargers. Therefore, implementing a network of 150 kW chargers is less costly.
- Building a network of 150 kW chargers when the vehicles cannot accept a 150 kW power, would still support the feasibility of trips in urban areas, while resulting in longer delays.
- The total length of the roadway is the main factor affecting the number of charging stations.
- The number of generated trips and the total length of the roadways affect the number of chargers.
- The battery size does not affect the number of chargers, as the length of the urban trips is significantly lower than the range of the EVs.
- The suggested numbers and locations are based on a predicted 6 percent market penetration rate in 2030. It is suggested that the city planners start building the network of charging stations in increments and track the utilization rate at each location before proceeding with full deployment. Detailed analysis for the annual increments can be done for each urban area per request.

The optimization-based modeling framework designed and proposed in this study finds the location of charging stations and number of chargers for the major urban areas in the state of Michigan, listed as: Muskegon, Ann Arbor, Kalamazoo, Flint, Saginaw, Lansing, Grand Rapids, and Detroit. As all of the major urban areas are located in lower peninsula, Marquette, the largest city in the upper peninsula is added to the list for the detailed analysis. The number of stations for the different scenarios for these cities ranges between 3-62 stations and 8-636 chargers. Aggregate level regression models are developed to find the number of charging stations and chargers in the smaller cities, with limited data availability, such as: Menominee, Sault Ste. Marie, Escanaba, Houghton, Traverse City, Battle Creek, Jackson, Port Huron, and Holland. The models proposed in this study can be used for other cities based-on availability of data as the need arises. The number of stations for the 150 kW charger and 70 kWh battery scenario for these cities ranges between 4-11 stations and 8-22 chargers.

REFERENCES

Andrews, M., Do˘ Gru, M.K., Hobby, J.D., Jin, Y., Tucci, G.H., 2012. Modeling and Optimization for Electric Vehicle Charging Infrastructure.

Atlas EV Hub, 2018. Market Data [WWW Document].

Bai, Y., Hwang, T., Kang, S., Ouyang, Y., 2011. Biofuel refinery location and supply chain planning under traffic congestion. Transp. Res. Part B Methodol. 45, 162–175. https://doi.org/10.1016/J.TRB.2010.04.006

Baouche, F., Billot, R., Trigui, R., El Faouzi, N.E., 2014. Efficient allocation of electric vehicles charging stations: Optimization model and application to a dense urban network. IEEE Intell. Transp. Syst. Mag. 6, 33–43. https://doi.org/10.1109/MITS.2014.2324023

Barnston, A.G., 1992. Correspondence among the correlation, RMSE, and Heidke Foresast verification measures; Refinement of the Heidke Score. Weather Forecast. 7, 699–709. https://doi.org/10.1175/1520-0434(1992)007<0699:CATCRA>2.0.CO;2

Berman, O., Larson, R.C., Fouska, N., 1992. Optimal Location of Discretionary Service Facilities. Transp. Sci. 26, 201–211.

Cai, H., Jia, X., Chiu, A.S.F., Hu, X., Xu, M., 2014. Siting public electric vehicle charging stations in Beijing using big-data informed travel patterns of the taxi fleet. Transp. Res. Part D Transp. Environ. 33, 39–46. https://doi.org/10.1016/j.trd.2014.09.003

Cavadas, J., de Almeida Correia, G.H., Gouveia, J., 2015. A MIP model for locating slow-charging stations for electric vehicles in urban areas accounting for driver tours. Transp. Res. Part E Logist. Transp. Rev. 75, 188–201. https://doi.org/10.1016/j.tre.2014.11.005

Chen, Z., Liu, W., Yin, Y., 2017. Deployment of stationary and dynamic charging infrastructure for electric vehicles along traffic corridors. Transp. Res. Part C Emerg. Technol. 77, 185–206. https://doi.org/10.1016/j.trc.2017.01.021

Dana Lowell, Brian Jones, and D.S., 2017. Electric Vehicle Cost-Benefit Analysis Plug-in Electric Vehicle Cost-Benefit Analysis: Michigan.

Dong, J., Liu, C., Lin, Z., 2014. Charging infrastructure planning for promoting battery electric vehicles: An activity-based approach using multiday travel data. Transp. Res. Part C Emerg. Technol. 38, 44–55. https://doi.org/10.1016/J.TRC.2013.11.001

Eberhard, M., Tarpenning, M., 2006. The 21 st Century Electric Car.

Eppstein, M.J., Grover, D.K., Marshall, J.S., Rizzo, D.M., 2011. An agent-based model to study market penetration of plug-in hybrid electric vehicles. Energy Policy 39, 3789–3802. https://doi.org/10.1016/J.ENPOL.2011.04.007

Ghamami, M., Kavianipour, M., Zockaie, A., Hohnstadt, L., Ouyang, Y., 2019a. Refueling infrastructure planning in intercity networks considering route choice and travel time delay for mixed fleet of electric and conventional vehicles. Transp. Res. Part C.

Ghamami, M., Zockaie, A., Nie, Y. (Marco), 2016. A general corridor model for designing plug-in electric vehicle charging infrastructure to support intercity travel. Transp. Res. Part C Emerg. Technol. 68, 389–402. https://doi.org/10.1016/J.TRC.2016.04.016

Ghamami, M., Zockaie, A., Wang, J., Miller, S., Kavianipour, M., Shojaie, M., Fakhrmoosavi, F., Hohnstadt, L., Singh, H., 2019b. Electric Vehicle Charger Placement Optimization in Michigan: Phase I – Highways.

Grassmann, W., 1983. The Convexity of the Mean Queue Size of the M/M/c Queue with Respect to the Traffic, Source: Journal of Applied Probability.

Hajibabai, L., Bai, Y., Ouyang, Y., 2014. Joint optimization of freight facility location and pavement infrastructure rehabilitation under network traffic equilibrium. Transp. Res. Part B Methodol. 63, 38–52. https://doi.org/10.1016/J.TRB.2014.02.003

He, F., Wu, D., Yin, Y., Guan, Y., 2013. Optimal deployment of public charging stations for plug-in hybrid electric vehicles. Transp. Res. Part B Methodol. 47, 87–101. https://doi.org/10.1016/J.TRB.2012.09.007

He, F., Yin, Y., Zhou, J., 2015. Deploying public charging stations for electric vehicles on urban road networks. Transp. Res. Part C Emerg. Technol. 60, 227–240. https://doi.org/10.1016/j.trc.2015.08.018

He, J., Yang, H., Tang, T.-Q., Huang, H.-J., 2018. An optimal charging station location model with the consideration of electric vehicle's driving range. Transp. Res. Part C Emerg. Technol. 86, 641–654. https://doi.org/10.1016/J.TRC.2017.11.026

He, S.Y., Kuo, Y.H., Wu, D., 2016. Incorporating institutional and spatial factors in the selection of the optimal locations of public electric vehicle charging facilities: A case study of Beijing, China. Transp. Res. Part C Emerg. Technol. 67, 131–148. https://doi.org/10.1016/j.trc.2016.02.003

Hodgson, M.J., 1990. A Flow-Capturing Location-Allocation Model. Geogr. Anal. 22, 270–279.

https://doi.org/10.1111/j.1538-4632.1990.tb00210.x

Huang, Y., Li, S., Qian, Z.S., 2015. Optimal Deployment of Alternative Fueling Stations on Transportation Networks Considering Deviation Paths. Networks Spat. Econ. 15, 183–204. https://doi.org/10.1007/s11067-014-9275-1

Huang, Y., Zhou, Y., 2015. An optimization framework for workplace charging strategies. Transp. Res. Part C Emerg. Technol. 52, 144–155. https://doi.org/10.1016/j.trc.2015.01.022

Jayakrishnan, R., Mahmassani, H.S., Hu, T.-Y., 1994. An evaluation tool for advanced traffic information and management systems in urban networks. Transp. Res. Part C Emerg. Technol. 2, 129–147.

Kang, J.E., Recker, W.W., 2009. An activity-based assessment of the potential impacts of plug-in hybrid electric vehicles on energy and emissions using 1-day travel data. Transp. Res. Part D Transp. Environ. 14, 541–556. https://doi.org/10.1016/j.trd.2009.07.012

Kavianipour, M., Zockaie, A., Ghamami, M., 2020. Urban Charging Planning Considering Range Anxiety and Users Delay.

Krisher, T., 2019. AAA: Cold weather can cut electric car range over 40 percent [WWW Document]. URL https://apnews.com/04029bd1e0a94cd59ff9540a398c12d1 (accessed 11.4.19).

Kuby, M., Lim, S., 2007. Location of Alternative-Fuel Stations Using the Flow-Refueling Location Model and Dispersion of Candidate Sites on Arcs. Networks Spat. Econ. 7, 129–152. https://doi.org/10.1007/s11067-006-9003-6

Kuby, M., Lim, S., 2005. The flow-refueling location problem for alternative-fuel vehicles. Socioecon. Plann. Sci. 39, 125–145. https://doi.org/10.1016/J.SEPS.2004.03.001

Li, S., Huang, Y., Mason, S.J., 2016. A multi-period optimization model for the deployment of public electric vehicle charging stations on network. Transp. Res. Part C Emerg. Technol. 65, 128–143. https://doi.org/10.1016/j.trc.2016.01.008

Lim, S., Kuby, M., 2010. Heuristic algorithms for siting alternative-fuel stations using the Flow-Refueling Location Model. Eur. J. Oper. Res. 204, 51–61. https://doi.org/10.1016/J.EJOR.2009.09.032

Lin, C., Choy, K.L., Ho, G.T.S., Chung, S.H., Lam, H.Y., 2014. Survey of Green Vehicle Routing Problem: Past and future trends. Expert Syst. Appl. 41, 1118–1138. https://doi.org/10.1016/J.ESWA.2013.07.107

Lin, Z., Greene, D., 2010. Who Will More Likely Buy PHEV: A Detailed Market Segmentation Analysis The 25th World Battery, Hybrid and Fuel Cell Electric Vehicle Symposium & Exhibition Who Will More Likely Buy PHEV: A Detailed Market Segmentation Analysis.

Lin, Z., Greene, D.L., 2011. Promoting the Market for Plug-In Hybrid and Battery Electric Vehicles. Transp. Res. Rec. J. Transp. Res. Board 2252, 49–56. https://doi.org/10.3141/2252-07

Listen Data, 2019. Difference between Adjusted R-squared and R-squared [WWW Document].

Mak, H.Y., Rong, Y., Shen, Z.J.M., 2013. Infrastructure planning for electric vehicles with battery swapping. Manage. Sci. 59, 1557–1575. https://doi.org/10.1287/mnsc.1120.1672

Mirhassani, S.A., Ebrazi, R., 2013. A Flexible Reformulation of the Refueling Station Location Problem. Transp. Sci. 47, 617–628. https://doi.org/10.1287/trsc.1120.0430

Nicholas, M.A., Handy, S.L., Sperling, D., 2004. Using Geographic Information Systems to Evaluate Siting and Networks of Hydrogen Stations, Transportation Research Record: Journal of the Transportation Research.

Nie, Y. (Marco), Ghamami, M., 2013. A corridor-centric approach to planning electric vehicle charging infrastructure. Transp. Res. Part B Methodol. 57, 172–190. https://doi.org/10.1016/J.TRB.2013.08.010

Nie, Y., Ghamami, M., Zockaie, A., Xiao, F., 2016. Optimization of incentive polices for plug-in electric vehicles. Transp. Res. Part B Methodol. https://doi.org/10.1016/j.trb.2015.12.011

Nourbakhsh, S.M., Ouyang, Y., 2010. Optimal fueling strategies for locomotive fleets in railroad networks. Transp. Res. Part B Methodol. https://doi.org/10.1016/j.trb.2010.03.003

NRC, 2013. Transitions to alternative vehicles and fuels, Transitions to Alternative Vehicles and Fuels. National Academies Press. https://doi.org/10.17226/18264

Philippe Crist, 2012. Electric Vehicles Revisited-Costs, Subsidies and Prospects.

Riemann, R., Wang, D.Z.W., Busch, F., 2015. Optimal location of wireless charging facilities for electric vehicles: Flow capturing location model with stochastic user equilibrium. Transp. Res. Part C Emerg. Technol. https://doi.org/10.1016/j.trc.2015.06.022

Shafiei, E., Thorkelsson, H., Ásgeirsson, E.I., Davidsdottir, B., Raberto, M., Stefansson, H., 2012. An agent-based modeling approach to predict the evolution of market share of electric vehicles: A case study from Iceland. Technol. Forecast. Soc. Change 79, 1638–1653. https://doi.org/10.1016/j.techfore.2012.05.011

Shahraki, N., Cai, H., Turkay, M., Xu, M., 2015. Optimal locations of electric public charging stations using real world vehicle travel patterns. Transp. Res. Part D Transp. Environ. 41, 165–176. https://doi.org/10.1016/j.trd.2015.09.011

Tu, W., Li, Q., Fang, Z., Shaw, S. lung, Zhou, B., Chang, X., 2016. Optimizing the locations of electric taxi charging stations: A spatial–temporal demand coverage approach. Transp. Res. Part C Emerg. Technol. 65, 172–189. https://doi.org/10.1016/j.trc.2015.10.004

Upchurch, C., Kuby, M., Lim, S., 2009. A model for location of capacitated alternative-fuel stations. Geogr. Anal. 41, 127–148. https://doi.org/10.1111/j.1538-4632.2009.00744.x

Wilaby, M., Casas, J., 2016. MI Travel Counts III.

Yang, J., Dong, J., Hu, L., 2017. A data-driven optimization-based approach for siting and sizing of electric taxi charging stations. Transp. Res. Part C Emerg. Technol. 77, 462–477.

https://doi.org/10.1016/j.trc.2017.02.014

Zhu, Z., Gao, Z., Zheng, J., Du, H., 2018. Charging Station Planning for Plug-In Electric Vehicles. J. Syst. Sci. Syst. Eng. 27, 24–45. https://doi.org/10.1007/s11518-017-5352-6

Zockaie, A., Aashtiani, H.Z., Ghamami, M., Marco Nie, Y., 2016. Solving Detour-Based Fuel Stations Location Problems. Comput. Civ. Infrastruct. Eng. 31, 132–144. https://doi.org/10.1111/mice.12170

Zukerman, M., 2013. Introduction to Queueing Theory and Stochastic Teletraffic Models.

APPENDIX A- CITY OF ANN ARBOR WITH EXTERNAL DEMAND

A large portion of the demand for the city of Ann Arbor travels to and from outside the city and its vicinity boundaries. Thus, the analysis for the city of Ann Arbor is taken further to include the external demand, traveling to and from outside the city and its vicinity boundaries. The original results are presented in the main body of the report, and this Appendix presents the results for the city of Ann Arbor with the external demand.

Table 20. Scenario results for the city of Ann Arbor with external demand: charging stations, chargers, required investment, and charge time

Scenario	1	2	3	4
Battery size (kWh)	70	100	70	100
Charging power (kW)	50	50	150	150
Number of zones	36	36	36	36
EV trips per day	18,162	18,162	18,162	18,162
Number of stations	8	6	7	6
Number of chargers	77	62	29	25
Station cost (Million dollar)	2.17	1.63	2.13	1.82
Charger cost (Million dollar)	2.98	2.41	2.35	2.04
Total infrastructure cost (Million dollar)	5.15	4.05	4.47	3.86
Average charging and queuing delay (min)	13.31	17.22	4.67	6.02

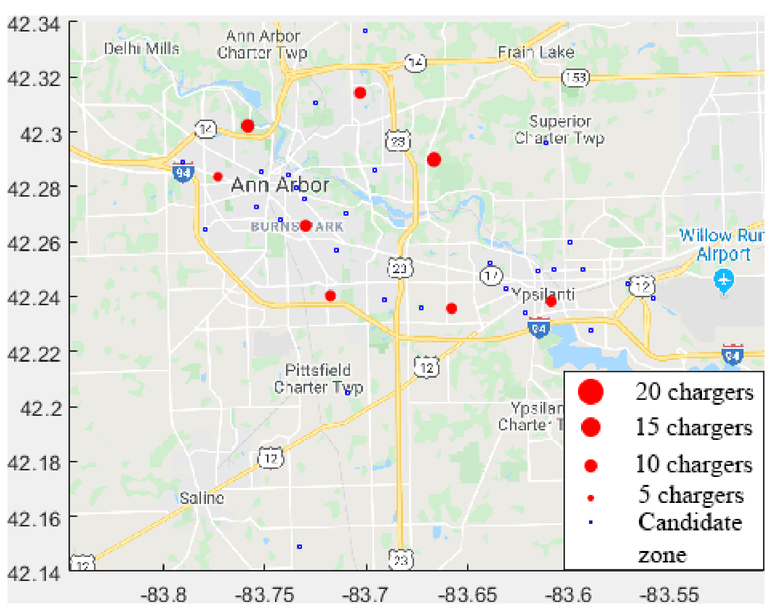


Figure 43. 70 kWh battery-50 kW charger configuration for the city of Ann Arbor with external demand

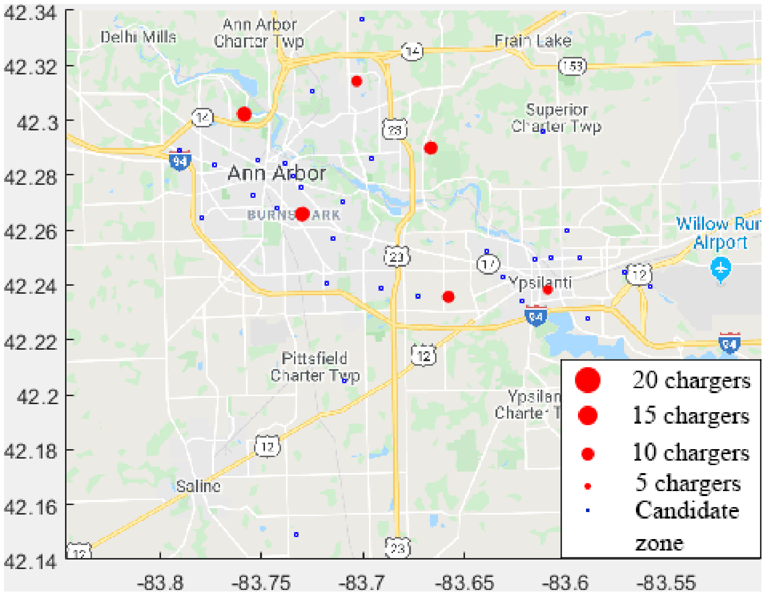


Figure 44. 100 kWh battery-50 kW charger configuration for the city of Ann Arbor with external demand

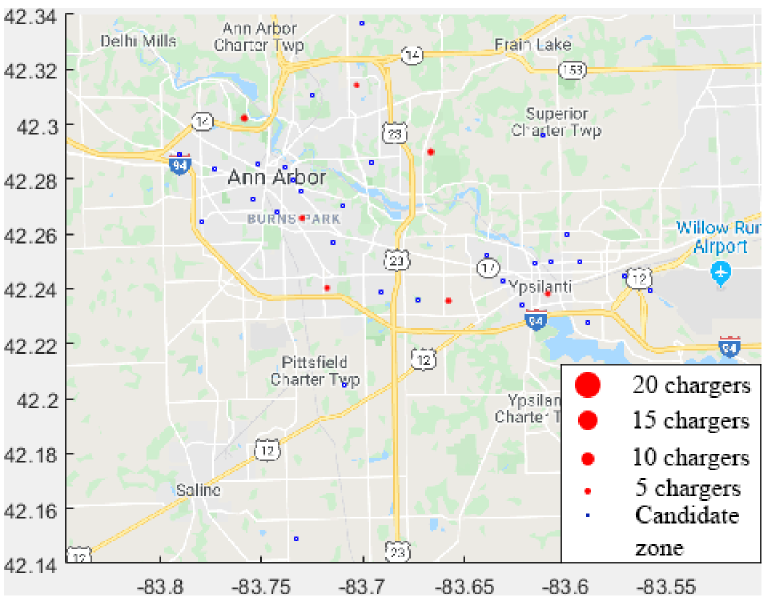


Figure 45. 70 kWh battery-150 kW charger configuration for the city of Ann Arbor with external demand

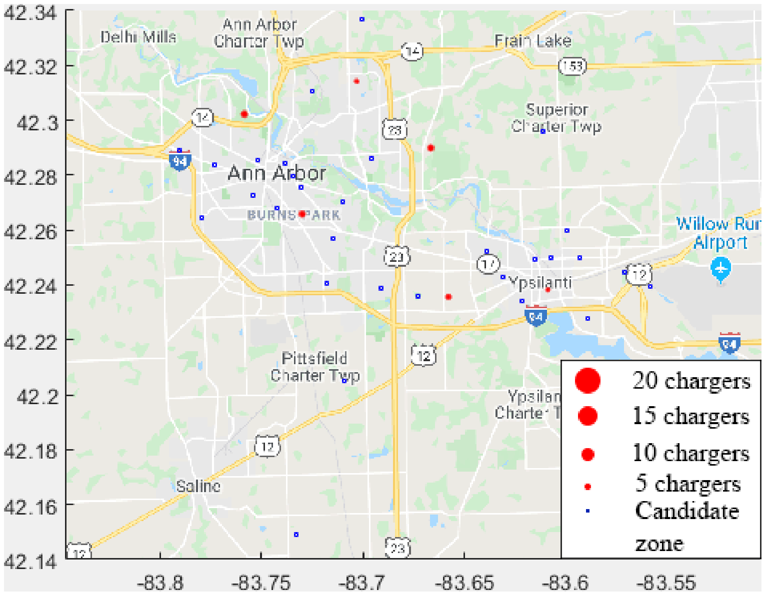


Figure 46. 100 kWh battery-150 kW charger configuration for the city of Ann Arbor with external demand

APPENDIX B- CHARGING STATION LOCATION AND NUMBER IN EACH URBAN AREA

Marquette

			Scenario			
Latitude	Longitude	Community	1	2	3	4
46.54678	-87.3902	Marquette	0	0	0	0
46.57084	-87.4003	Marquette	4	7	0	3
46.56068	-87.417	Marquette	0	0	0	0
46.54954	-87.4174	Marquette	0	0	0	0
46.55185	-87.3902	Marquette	4	0	2	0
46.52007	-87.4018	Marquette	0	0	0	0
46.52309	-87.7107	Ishpeming Township	0	0	0	0
46.44223	-87.7189	Ishpeming Township	0	0	0	0
46.50204	-87.6242	Negaunee	0	0	0	0
46.5055	-87.5992	Negaunee	0	0	0	0
46.49705	-87.6777	Ishpeming Township	3	3	2	2
46.50255	-87.6522	Ishpeming Township	0	0	0	0
46.47787	-87.6756	Ishpeming Township	0	0	0	0
46.56645	-87.551	Marquette	4	4	2	2
46.50961	-87.502	Negaunee	0	0	0	0
46.58569	-87.4521	Marquette	0	0	0	0
46.52917	-87.466	Marquette	0	0	0	0
46.42566	-87.543	Richmond Township	0	0	0	0
46.40284	-87.4452	Sands Township	0	0	0	0
46.46371	-87.2904	Chocolay Charter Twp	0	0	0	0
46.29666	-87.3944	Forsyth Township	4	2	2	2

Muskegon

Latitude	Longitude	Community	Scenario 1	2	3	4
43.2279	-86.2549	Muskegon	3	5	0	0
43.25468	-86.2424	Muskegon	0	0	0	0
43.24132	-86.2132	Muskegon	0	0	0	0
43.21585	-86.2069	Muskegon	0	0	0	0
43.23625	-86.2349	Muskegon	0	0	0	0
43.22256	-86.2497	Muskegon	0	0	0	0
43.22767	-86.2713	Muskegon	0	0	0	0
43.21224	-86.2742	Muskegon	0	0	0	0
43.20648	-86.3096	Muskegon	0	0	0	0
43.20912	-86.2573	Muskegon Heights	5	6	2	4
43.20845	-86.2363	Muskegon Heights	6	7	3	0
43.19437	-86.255	Muskegon Heights	0	0	0	0
43.41524	-86.3696	Montague	0	0	0	0
43.43831	-86.4388	White River Township	0	0	0	0
43.45452	-86.3219	Montague	0	0	0	0
43.40452	-86.3374	Whitehall Township	3	3	2	2
43.41642	-86.2967	Whitehall Township	0	0	0	0
43.34882	-86.3589	Fruitland Township	0	0	0	0
43.43178	-86.1984	Blue Lake Township	0	0	0	0
43.4529	-86.0702	Holton Township	0	0	0	0
43.32395	-86.2021	Muskegon	0	0	0	0
43.36241	-86.2133	Dalton Township	3	3	2	0
43.32862	-86.0791	Cedar Creek	0	0	0	0
43.28963	-86.3745	Laketon Township	0	0	0	0
43.26744	-86.2943	Laketon Township	0	0	0	0
43.25076	-86.2846	North Muskegon	6	6	3	3
43.22835	-86.1941	Muskegon Charter Township	8	7	3	4
43.27	-86.2222	Muskegon Charter Township	0	0	0	0
43.2511	-86.1636	Muskegon Charter Township	0	0	0	0
43.22518	-86.1623	Muskegon Charter Township	0	0	0	0
43.22159	-86.1004	Egelston Township	0	0	0	0
43.24847	-86.1152	Muskegon	0	0	0	0
43.18288	-86.2807	Norton Shores	0	0	0	0

Muskegon

			Scenario			
Latitude	Longitude	Community	1	2	3	4
43.18422	-86.301	Norton Shores	0	0	0	0
43.19291	-86.2116	Norton Shores	0	0	0	0
43.16974	-86.2383	Norton Shores	0	0	0	0
43.1403	-86.2405	Norton Shores	5	5	2	2
43.20119	-86.278	Muskegon	0	0	0	0
43.13824	-86.1629	Fruitport Charter Twp	0	0	0	0
43.12558	-86.1628	Fruitport Charter Twp	0	0	0	0
43.1745	-86.1915	Fruitport Charter Twp	0	0	0	0
43.15997	-86.0413	Fruitport Charter Twp	0	0	0	0
43.0735	-86.1947	Spring Lake	5	6	2	3
43.10969	-86.2465	Spring Lake	0	0	0	0
43.06291	-86.1786	Spring Lake	0	0	0	0
43.0839	-86.2398	Ferrysburg	0	0	0	0
43.0693	-86.2294	Grand Haven	0	0	0	0
43.05309	-86.2251	Grand Haven	0	0	0	0
43.05897	-86.2176	Grand Haven	0	0	0	0
43.10681	-86.0822	Fruitport Charter Twp	0	0	0	0
43.0271	-86.174	Grand Haven	0	0	0	0
43.02365	-86.0556	Robinson Township	0	0	0	0

Ann Arbor

			Scenario							
			Without External Demand				With External Demand			
Latitude	Longitude	Community	1	2	3	4	1	2	3	4
42.285364	-83.752092	Ann Arbor	0	0	0	0	0	0	0	0
42.302203	-83.758589	Ann Arbor	0	0	0	0	11	12	5	5
42.310808	-83.72524	Washtenaw County	0	0	0	0	0	0	0	0
42.314174	-83.703167	Ann Arbor	0	8	0	3	10	9	3	3
42.285994	-83.695971	Ann Arbor	0	0	0	0	0	0	0	0
42.288943	-83.790464	Ann Arbor	0	0	0	0	0	0	0	0
42.283684	-83.773269	Ann Arbor	0	0	0	0	7	0	0	0
42.284251	-83.738223	Ann Arbor	0	0	0	0	0	0	0	0
42.279807	-83.734635	Ann Arbor	0	0	0	0	0	0	0	0
42.275733	-83.730341	Ann Arbor	0	0	0	0	0	0	0	0
42.264346	-83.77922	Ann Arbor Charter Twp	0	0	0	0	0	0	0	0
42.27254	-83.753972	Ann Arbor	0	0	0	0	0	0	0	0
42.268156	-83.74258	Ann Arbor	0	0	0	0	0	0	0	0
42.265812	-83.730071	Ann Arbor	11	12	4	4	10	12	4	5
42.270599	-83.710118	Ann Arbor	0	0	0	0	0	0	0	0
42.240353	-83.717784	Ann Arbor	0	0	0	0	9	0	4	0
42.256726	-83.714557	Ann Arbor	0	0	0	0	0	0	0	0
42.238845	-83.691264	Ann Arbor	0	0	0	0	0	0	0	0
42.336734	-83.701037	Ann Arbor Charter Twp	0	0	0	0	0	0	0	0
42.289888	-83.666696	Ann Arbor Charter Twp	5	0	2	0	12	11	5	5
42.296013	-83.611355	Superior Charter Twp	0	0	0	0	0	0	0	0
42.204863	-83.709303	Pittsfield Charter Twp	0	0	0	0	0	0	0	0
42.236151	-83.672814	Pittsfield Charter Twp	0	0	0	0	0	0	0	0
42.233939	-83.621701	Ypsilanti	0	0	0	0	0	0	0	0
42.252507	-83.639179	Ypsilanti	8	9	0	0	0	0	0	0
42.249126	-83.615031	Ypsilanti	0	0	0	0	0	0	0	0
42.249659	-83.607499	Ypsilanti	0	0	0	0	0	0	0	0
42.243108	-83.630933	Ypsilanti	0	0	0	0	0	0	0	0

Ann Arbor

			Scenario							
			Without External Demand				With External Demand			
Latitude	Longitude	Community	1	2	3	4	1	2	3	4
42.238236	-83.609043	Ypsilanti	0	0	0	0	9	8	4	3
42.250113	-83.593108	Ypsilanti Charter Twp	0	0	0	0	0	0	0	0
42.259775	-83.599841	Ypsilanti Charter Twp	0	0	0	0	0	0	0	0
42.24491	-83.571363	Ypsilanti Charter Twp	0	0	0	0	0	0	0	0
42.239571	-83.558834	Ypsilanti Charter Twp	0	0	0	0	0	0	0	0
42.227682	-83.589045	Ypsilanti Charter Twp	0	0	0	0	0	0	0	0
42.235676	-83.658011	Ypsilanti Charter Twp	0	0	4	4	9	10	4	4
42.149146	-83.732635	York Charter Twp	0	0	0	0	0	0	0	0

Kalamazoo

Latitude	Longitude	Community	Scenario 1	2	3	4
42.29819	-85.5844	Kalamazoo	0	0	0	0
42.3167	-85.5588	Kalamazoo	0	0	0	0
42.30837	-85.5973	Kalamazoo	0	0	0	0
42.2981	-85.6057	Kalamazoo	3	0	0	0
42.30033	-85.5647	Kalamazoo	6	8	3	4
42.28088	-85.6407	Kalamazoo	0	0	0	0
42.284	-85.6176	Kalamazoo	5	7	3	3
42.28086	-85.594	Kalamazoo	0	0	0	0
42.28848	-85.5746	Kalamazoo	0	0	0	0
42.27218	-85.5842	Kalamazoo	5	5	0	0
42.27509	-85.5586	Kalamazoo	0	0	0	0
42.26754	-85.5969	Kalamazoo	0	0	0	0
42.26322	-85.5521	Kalamazoo	4	5	2	2
42.25676	-85.6276	Kalamazoo	0	0	0	0
42.25336	-85.6078	Kalamazoo	0	0	0	0
42.25632	-85.5474	Kalamazoo	0	0	0	0
42.32741	-85.5629	Parchment	4	4	2	0
42.32523	-85.6088	Kalamazoo Twp	0	0	0	0
42.30043	-85.6331	Kalamazoo Twp	0	0	0	0
42.30738	-85.5417	Kalamazoo Twp	0	0	0	0
42.28063	-85.5407	Kalamazoo Twp	0	0	0	0
42.32129	-85.7157	Oshtemo Township	0	0	0	0
42.26744	-85.7158	Oshtemo Township	5	5	3	2
42.3578	-85.6822	Alamo Township	0	0	0	0
42.34859	-85.5169	Cooper Twp	0	0	0	0
42.35832	-85.6372	Cooper Twp	0	0	0	0
42.35691	-85.5696	Cooper Twp	0	0	0	0
42.34153	-85.564	Cooper Twp	0	0	0	0
42.27416	-85.4754	Comstock Twp	0	0	0	0
42.31436	-85.5015	Comstock Twp	0	0	0	0
42.29757	-85.5228	Comstock Twp	0	0	0	0
42.17708	-85.7406	Texas Charter Township	0	0	0	0
42.13464	-85.7384	Prairie Ronde Township	0	0	0	0
42.2117	-85.6075	Portage	4	4	2	2
42.24048	-85.6026	Portage	8	8	4	4

Kalamazoo

			Scenario			
Latitude	Longitude	Community	1	2	3	4
42.2094	-85.5805	Portage	0	0	0	0
42.22752	-85.5341	Portage	4	4	0	0
42.21767	-85.6304	Portage	0	0	0	0
42.17366	-85.5877	Portage	0	0	0	0
42.11813	-85.5389	Vicksburg	0	0	0	0
42.1166	-85.6437	Schoolcraft Township,	0	0	0	0
42.1372	-85.6172	Schoolcraft Township,	0	0	0	0
42.23022	-85.4555	Pavilion Township	0	0	0	0
42.14362	-85.4356	Brady Township	0	0	0	0
42.2101	-85.8979	Paw Paw	0	0	0	0
42.17394	-85.9393	Paw Paw	4	4	2	2
42.27865	-85.9211	Waverly Township,	0	0	0	0
42.2731	-85.8322	Almena Township	0	0	0	0
42.1622	-85.8547	Lawton	0	0	0	0
42.20853	-85.7977	Mattawan	3	3	0	0
42.24025	-85.8421	Antwerp Township	0	0	0	0
42.18444	-85.8246	Antwerp Township	0	0	0	0
42.10468	-85.9703	Decatur	0	0	0	0
42.12207	-85.9446	Decatur	0	0	0	0
42.08883	-85.8361	Porter Township	0	0	0	0

Flint

Latitude	Longitude	Community	Scenario 1	2	3	4
43.01339	-83.6913	Flint	0	0	0	0
43.06708	-83.7225	Flint	0	0	0	0
43.07254	-83.6985	Flint	0	0	0	0
43.0672	-83.701	Flint	4	4	2	0
43.06912	-83.6641	Flint	0	0	0	0
43.06052	-83.6568	Flint	0	5	0	3
43.05262	-83.7251	Flint	0	0	0	0
43.05659	-83.701	Flint	0	0	0	0
43.04948	-83.7089	Flint	0	0	0	0
43.0555	-83.6895	Flint	0	0	0	0
43.04244	-83.7239	Flint	0	0	0	0
43.03615	-83.724	Flint	0	0	0	3
43.04289	-83.7009	Flint	0	0	0	0
43.03677	-83.7107	Flint	0	0	0	0
43.04218	-83.6831	Flint	0	0	0	0
43.04012	-83.6683	Flint	5	0	2	0
43.04558	-83.6454	Flint	0	0	0	0
43.02804	-83.6394	Flint	0	0	0	0
43.02945	-83.6616	Flint	0	0	0	0
43.02828	-83.7372	Flint	0	0	0	0
43.02363	-83.7146	Flint	0	0	0	0
43.01662	-83.7017	Flint	0	0	0	0
43.02822	-83.6965	Flint	5	5	0	0
43.02762	-83.6754	Flint	0	0	0	0
43.02032	-83.6812	Flint	0	0	0	0
43.02297	-83.6594	Flint	0	0	0	0
43.00666	-83.7279	Flint	0	0	0	0
43.00874	-83.7019	Flint	0	0	0	0
43.00194	-83.6866	Flint	6	6	3	4
43.00553	-83.6723	Flint	0	0	0	0
43.00695	-83.6474	Flint	8	10	4	5
42.99812	-83.7298	Flint	6	9	3	0
42.96791	-83.744	Flint	0	0	0	0
42.99123	-83.6898	Flint	0	0	0	0
42.99303	-83.6712	Flint	0	0	0	0
42.99362	-83.6498	Flint	0	0	0	0
43.17124	-83.8896	Montrose	0	0	0	0

Flint

Latitude	Longitude	Community	Scenario 1	2	3	4
43.1936	-83.8283	Montrose	0	0	0	0
43.18251	-83.7416	Clio	4	0	2	0
43.15722	-83.8007	Vienna Twp	0	0	0	0
43.07022	-83.849	Flushing Township	0	0	0	0
43.08739	-83.9142	Flushing Township	0	0	0	0
43.09251	-83.8466	Flushing Township	3	5	2	2
43.0983	-83.8036	Mt Morris Township	0	0	0	0
43.0705	-83.7945	Mt Morris Township	0	0	0	0
43.134	-83.7145	Mt Morris Township	0	0	0	0
43.09819	-83.716	Mt Morris Township	0	0	0	0
43.08641	-83.7213	Mt Morris Township	0	0	0	0
43.1232	-83.7019	Mt Morris Township	0	0	0	0
43.12936	-83.6466	Genesee Charter Township	4	5	2	2
43.10325	-83.6603	Genesee Charter Township	0	0	0	0
43.06563	-83.6225	Genesee Charter Township	0	0	0	0
43.07146	-83.5985	Genesee Charter Township	0	0	0	0
43.0581	-83.5459	Richfield Township	0	0	0	0
43.03091	-83.511	Davison	0	0	0	0
43.01442	-83.53	Davison	4	4	2	0
42.96611	-83.6102	Burton	0	0	0	0
43.04462	-83.5996	Burton	0	0	0	0
42.99735	-83.5806	Burton	0	0	0	0
43.0021	-83.6205	Burton	0	0	0	0
42.96871	-83.6568	Burton	6	7	3	3
42.96364	-83.6883	Burton	0	0	0	0
42.98613	-83.7857	Flint Twp	8	10	4	4
43.01764	-83.8032	Flint Twp	0	0	0	0
43.04457	-83.7653	Flint Twp	0	0	0	0
43.02083	-83.7586	Flint Twp	5	0	0	0
42.98966	-83.7696	Flint Twp	0	0	0	0
42.96627	-83.7134	Flint Twp	0	0	0	0
42.97518	-83.9016	Clayton Twp	0	0	0	0
42.95091	-83.8546	Swartz Creek	0	0	0	0

Flint

Latitude	Longitude	Community	Scenario 1	2	3	4
42.8928	-83.8049	Mundy Township	0	0	0	0
42.95049	-83.7154	Flint Twp	0	0	0	0
42.93715	-83.9048	Gaines Township	0	0	0	0
42.93167	-83.6147	Grand Blanc	0	0	0	0
42.93171	-83.6746	Grand Blanc	0	0	0	0
42.95734	-83.616	Grand Blanc	0	0	0	0
42.90788	-83.6368	Grand Blanc	0	0	0	0
42.90287	-83.673	Grand Blanc	0	0	0	0
42.88006	-83.5272	Atlas Township	0	0	0	0
43.20801	-83.9525	Maple Grove Township	0	0	0	0
42.96957	-83.9649	Venice Township	3	3	2	0
43.07661	-83.9644	Hazelton Township	0	0	0	0
42.91677	-83.9937	Durand	0	0	0	0
42.93642	-83.9721	Vernon Township	0	0	0	0

Saginaw

Latitude	Longitude	Community	Scenario 1	2	3	4
43.59069	-83.8925	Bay City	0	0	0	0
43.6057	-83.9077	Bay City	6	8	3	4
43.61652	-83.8916	Bay City	0	0	0	0
43.60609	-83.8764	Bay City	4	5	0	0
43.60033	-83.9039	Bay City	7	8	3	3
43.59956	-83.877	Bay City	0	0	0	0
43.60164	-83.8619	Bay City	4	5	2	2
43.59433	-83.8794	Bay City	0	0	0	0
43.58422	-83.9081	Bay City	0	0	0	0
43.58448	-83.8934	Bay City	0	0	0	0
43.58422	-83.8808	Bay City	0	0	0	0
43.57065	-83.8835	Bay City	0	0	0	0
43.56515	-83.9008	Bay City	0	0	0	0
43.60915	-83.8436	Essexville	0	0	0	0
43.78442	-84.1059	Linwood	0	0	0	0
43.78304	-83.9577	Fraser Township	0	0	0	0
43.61379	-83.9252	Bangor Charter Twp	0	0	0	0
43.66124	-83.9075	Bangor Charter Twp	0	0	0	0
43.63451	-83.8893	Bangor Charter Twp	0	0	0	0
43.59923	-84.0824	Auburn	8	7	3	3
43.68505	-84.1419	Beaver Township	0	0	0	0
43.70851	-84.041	Kawkawlin	0	0	0	0
43.69142	-83.9431	Bangor Charter Twp	3	0	2	0
43.6281	-84.0684	Williams Charter Township	0	0	0	0
43.601	-84.122	Williams Charter Township	0	0	0	0
43.62567	-83.9813	Monitor Charter Township	0	0	0	0
43.58446	-83.9804	Monitor Charter Township	0	0	0	0
43.55455	-83.8653	Portsmouth Charter Township	0	0	0	0
43.56135	-83.9886	Bay City	0	0	0	0
43.60045	-83.8278	Hampton Twp	0	0	0	0
43.61126	-83.8067	Hampton Twp	0	0	0	0
43.54662	-83.7269	Merritt Township	0	0	0	0
43.40374	-84.4837	Breckenridge	0	0	0	0
43.4523	-84.4534	Wheeler Township	3	4	2	2
43.35517	-84.3876	Lafayette Township	0	0	0	0
43.73505	-83.4628	Sebewaing Township	0	0	0	0

Saginaw

Latitude	Longitude	Community	Scenario 1	2	3	4
43.70176	-83.4171	Sebewaing Township	3	3	2	2
43.60433	-84.2419	Midland	0	0	0	0
43.65107	-84.2732	Midland	0	0	0	0
43.65134	-84.2171	Midland	0	0	0	0
43.61643	-84.2763	Midland	0	0	0	0
43.63063	-84.2427	Midland	7	9	3	4
43.61657	-84.2232	Midland	6	8	3	3
43.61509	-84.1742	Midland	0	0	0	0
43.59759	-84.2033	Midland	0	0	0	0
43.65849	-84.4429	Jerome Township	0	0	0	0
43.77535	-84.4479	Edenville Township	3	0	2	0
43.68197	-84.326	Lincoln Township	0	0	0	0
43.79807	-84.3366	Hope Township	0	0	0	0
43.7805	-84.2761	Mills Township	0	0	0	0
43.68903	-84.2167	Larkin Charter Twp	0	0	0	0
43.59012	-84.4136	Lee Township	0	0	0	0
43.50438	-84.4627	Porter Township	0	0	0	0
43.58579	-84.2753	Midland	0	0	0	0
43.58989	-84.339	Homer Township	4	3	2	0
43.49773	-84.3464	Mt Haley Township	0	0	0	0
43.54918	-84.2123	Ingersoll Township	0	0	0	0
43.43567	-83.9353	Saginaw	0	5	0	0
43.45314	-83.9189	Saginaw	0	0	0	0
43.44085	-83.9828	Saginaw	5	0	0	0
43.43534	-83.9691	Saginaw	0	0	0	0
43.43142	-83.9559	Saginaw	0	0	0	0
43.43158	-83.9223	Saginaw	0	0	0	0
43.4296	-83.9791	Saginaw	0	0	0	0
43.42294	-83.9637	Saginaw	0	0	0	0
43.42419	-83.9383	Saginaw	4	0	2	0
43.41923	-83.9305	Saginaw	5	5	2	3
43.4214	-83.913	Saginaw	0	0	0	0
43.41155	-83.9852	Saginaw	0	0	0	0
43.39089	-83.9835	Saginaw	0	4	0	0
43.40956	-83.9771	Saginaw	0	0	0	0
43.39564	-83.9526	Saginaw	4	4	2	2
43.39684	-83.9427	Saginaw	0	0	0	0

Saginaw

Latitude	Longitude	Community	Scenario 1	2	3	4
43.40416	-83.9223	Saginaw	0	0	0	0
43.55606	-84.1071	Tittabawassee Township	0	0	0	0
43.42957	-84.0714	Thomas Township	0	0	0	0
43.44348	-84.121	Thomas Township	0	0	0	0
43.44438	-84.0167	Saginaw Charter Township	9	11	4	4
43.456	-84.0008	Saginaw Charter Township	0	0	0	0
43.42481	-84.0233	Saginaw Charter Township	0	0	0	0
43.40364	-84.0171	Saginaw Charter Township	0	0	0	0
43.49946	-83.9909	Saginaw Charter Township	5	5	2	2
43.46973	-83.9399	Carrollton Township	0	0	0	0
43.44311	-83.8998	Buena Vista Charter Township	0	0	0	0
43.40351	-83.8967	Buena Vista Charter Township	6	6	3	3
43.42519	-83.8525	Buena Vista Charter Township	0	0	0	0
43.49777	-83.909	Zilwaukee Township	4	4	2	2
43.43519	-83.7892	Blumfield Township	0	0	0	0
43.45192	-84.2101	Richland Township	3	0	0	0
43.43744	-84.3566	Jonesfield Township	0	0	0	0
43.37037	-84.3169	Lakefield Township	0	0	0	0
43.38001	-84.2048	Fremont Township	0	0	0	0
43.29938	-84.1635	St Charles Township	0	0	0	0
43.35705	-84.166	Swan Creek Township	3	4	2	2
43.35996	-84.0655	James Township	0	0	0	0
43.28846	-84.0014	Albee Township	0	0	0	0
43.33081	-84.0115	Bridgeport Charter Township	0	0	0	0
43.37563	-83.849	Bridgeport Charter Township	0	0	0	0
43.36841	-83.9091	Bridgeport Charter Township	0	0	0	0
43.32522	-83.7451	Frankenmuth	4	4	2	2
43.37777	-83.7781	Frankenmuth Township	0	0	0	0
43.2919	-83.7759	Birch Run Township	0	0	0	0
43.27188	-83.9082	Taymouth Township	3	3	2	0
43.28363	-84.2052	Brant Township	0	0	0	0

Saginaw

Latitude	Longitude	Community	Scenario 1	2	3	4
43.48154	-83.3984	Caro	0	0	0	0
43.44319	-83.409	Caro	3	4	2	2
43.44013	-83.5732	Juniata Township	0	0	0	0
43.62189	-83.4365	Columbia Township	3	0	0	0
43.58044	-83.6309	Wisner Township	0	0	0	0
43.67693	-83.5582	Akron Township	0	0	0	0
43.50105	-83.5	Fairgrove Township	0	0	0	0
43.49363	-83.668	Reese	0	0	0	0
43.53775	-83.4206	Almer Township	0	0	0	0
43.43307	-83.6651	Denmark Township	4	3	2	0
43.34823	-83.6801	Tuscola Township	0	0	0	0
43.37079	-83.5925	Vassar	0	0	0	0

Lansing

Latitude	Longitude	Community	Scenario 1	2	3	4
42.90225	-84.7484	Westphalia Township	0	0	0	0
42.8833	-84.5024	Olive Township	0	0	0	0
42.80791	-84.6474	Watertown Charter Township	6	7	3	4
42.89995	-84.625	Riley	0	0	0	0
42.79377	-84.8134	Eagle Township	0	0	0	0
42.83727	-84.5865	Dewitt	0	0	0	0
42.8196	-84.5706	Dewitt	0	0	0	0
42.79604	-84.5839	Watertown Charter Township	0	0	0	0
42.78144	-84.5029	East Lansing	0	0	0	0
42.77586	-84.4501	Bath Twp	0	0	0	0
42.84132	-84.4348	Bath Twp	0	0	0	0
42.57704	-84.8252	Charlotte	4	4	2	2
42.55883	-84.8551	Charlotte	0	0	0	0
42.54718	-84.8421	Charlotte	0	0	0	0
42.72067	-84.7661	Oneida Charter Twp	0	0	0	0
42.76027	-84.7499	Grand Ledge	0	0	0	0
42.74497	-84.7488	Grand Ledge	3	3	2	0
42.72865	-84.6768	Delta Charter Township	0	0	0	0
42.75722	-84.6282	Delta Charter Township	0	0	0	0
42.73363	-84.6249	Delta Charter Township	4	0	0	0
42.70741	-84.6227	Delta Charter Township	0	0	0	0
42.63515	-84.6855	Windsor Charter Township	0	0	0	0
42.55894	-84.7726	Eaton Township	0	0	0	0
42.63083	-84.7522	Potterville	0	0	0	0
42.64407	-84.772	Potterville	0	0	0	0
42.51939	-84.6437	Eaton Rapids	0	0	0	0
42.53214	-84.684	Eaton Rapids	0	0	0	0
42.74022	-84.5483	Lansing	0	0	0	0
42.76681	-84.5995	Lansing	0	0	0	0
42.76644	-84.5622	Lansing	0	0	0	0
42.74641	-84.5495	Lansing	0	0	0	0
42.75199	-84.5749	Lansing	0	0	0	0
42.74618	-84.552	Lansing	6	8	3	3
42.73748	-84.5762	Lansing	7	9	3	4
42.72908	-84.5735	Lansing	0	0	0	0

Lansing

Latitude	Longitude	Community	Scenario 1	2	3	4
42.74905	-84.5332	Lansing	0	0	0	0
42.73852	-84.5339	Lansing	0	0	0	0
42.74016	-84.5069	Lansing	0	0	0	0
42.72774	-84.5293	Lansing	6	8	0	3
42.72237	-84.5285	Lansing	0	0	0	0
42.70678	-84.595	Lansing	0	0	0	0
42.71632	-84.5725	Lansing	0	0	0	0
42.71894	-84.552	Lansing	0	0	0	0
42.7168	-84.5346	Lansing	0	0	0	0
42.69103	-84.5939	Lansing	8	9	4	4
42.69187	-84.5858	Lansing	0	0	0	0
42.69118	-84.5725	Lansing	0	0	0	0
42.70496	-84.5592	Lansing	0	0	0	0
42.69398	-84.5579	Lansing	0	0	0	0
42.69559	-84.5415	Lansing	0	0	0	0
42.70512	-84.5094	Lansing	0	0	0	0
42.67875	-84.5868	Lansing	0	0	0	0
42.67279	-84.5345	Lansing	6	6	3	3
42.74457	-84.5958	Lansing	0	0	0	0
42.73149	-84.5934	Lansing	0	0	0	0
42.75444	-84.5106	Lansing	5	6	3	0
42.74959	-84.5009	East Lansing	0	0	0	0
42.7658	-84.4949	East Lansing	0	0	0	0
42.75235	-84.4786	East Lansing	0	0	0	0
42.74089	-84.4985	East Lansing	0	0	0	0
42.74354	-84.4727	East Lansing	0	0	0	0
42.73887	-84.4817	East Lansing	0	0	0	0
42.73553	-84.4659	East Lansing	6	9	3	4
42.7306	-84.4778	East Lansing	0	0	0	0
42.72701	-84.5016	East Lansing	0	0	0	0
42.71769	-84.501	East Lansing	0	0	0	0
42.72337	-84.4778	East Lansing	0	0	0	0
42.71121	-84.4085	Meridian Charter Township	6	7	3	3
42.72088	-84.4447	Meridian Charter Township	0	0	0	0
42.76421	-84.4591	Meridian Charter Township	4	0	0	0
42.742	-84.3834	Meridian Charter Township	0	0	0	0
42.69108	-84.3998	Meridian Charter Township	8	8	3	3

Lansing

Latitude	Longitude	Community	Scenario 1	2	3	4
42.69191	-84.2693	Williamstown Township	0	0	0	0
42.71689	-84.3368	Williamstown Township	0	0	0	0
42.62103	-84.3347	Wheatfield Township	0	0	0	0
42.66364	-84.1834	Webberville	0	0	0	0
42.61329	-84.227	Leroy Township	0	0	0	0
42.7087	-84.1983	Locke Township	0	0	0	0
42.65153	-84.5171	Delhi Charter Township	0	0	0	0
42.6489	-84.5414	Delhi Charter Township	0	0	0	0
42.6665	-84.5028	Delhi Charter Township	0	0	0	0
42.61252	-84.5427	Delhi Charter Township	0	0	0	0
42.57031	-84.4254	Mason	0	0	0	0
42.57152	-84.4591	Mason	4	0	2	0
42.65184	-84.3897	Alaiedon Township	0	0	0	0
42.53862	-84.3733	Vevay Township	0	0	0	0
42.58836	-84.3365	Ingham Township	0	3	0	0
42.58708	-84.2402	White Oak Township	0	0	0	0
42.54631	-84.5162	Mason	0	0	0	0
42.82483	-84.2249	Perry	2	2	2	0
42.84121	-84.318	Woodhull Township	0	0	0	0
42.80567	-84.2134	Perry Township	0	0	0	0

Grand Rapids

			Scenario			
Latitude	Longitude	Community	1	2	3	4
42.96779	-85.6647	Grand Rapids	0	0	0	0
43.02619	-85.6398	Grand Rapids	0	0	0	0
43.00492	-85.6672	Grand Rapids	0	0	0	0
43.00677	-85.627	Grand Rapids	0	0	0	0
42.99409	-85.6252	Grand Rapids	6	8	3	3
42.99208	-85.6467	Grand Rapids	0	0	0	0
42.99094	-85.6695	Grand Rapids	6	0	0	0
42.99442	-85.7025	Grand Rapids	0	0	0	0
42.99128	-85.7355	Grand Rapids	0	0	0	0
42.97714	-85.7239	Grand Rapids	0	0	0	0
42.97808	-85.7061	Grand Rapids	0	0	0	0
42.97849	-85.6987	Grand Rapids	0	0	0	0
42.98104	-85.6815	Grand Rapids	9	11	5	6
42.97884	-85.6589	Grand Rapids	0	0	0	0
42.97741	-85.6455	Grand Rapids	0	0	0	0
42.96696	-85.6945	Grand Rapids	6	6	0	0
42.96015	-85.6987	Grand Rapids	0	0	0	0
42.96752	-85.6454	Grand Rapids	0	0	0	0
42.97306	-85.6187	Grand Rapids	0	0	0	0
42.95823	-85.6539	Grand Rapids	0	0	0	0
42.96013	-85.6347	Grand Rapids	0	0	0	0
42.94848	-85.6912	Grand Rapids	0	0	0	0
42.94256	-85.662	Grand Rapids	6	7	3	3
42.94492	-85.6435	Grand Rapids	0	0	0	0
42.94583	-85.6331	Grand Rapids	7	8	3	3
42.93392	-85.6744	Grand Rapids	0	0	0	0
42.93573	-85.6609	Grand Rapids	0	0	0	0
42.9347	-85.644	Grand Rapids	0	0	0	0
42.93302	-85.6278	Grand Rapids	0	0	0	0
42.92222	-85.6547	Grand Rapids	0	0	0	0
42.91982	-85.6415	Grand Rapids	0	0	0	0
42.92889	-85.591	Grand Rapids	7	7	0	0
42.90548	-85.6162	Grand Rapids	8	10	0	0
42.95355	-85.6057	East Grand Rapids	0	0	0	0
42.94321	-85.6263	East Grand Rapids	0	0	0	0
42.93685	-85.613	East Grand Rapids	0	0	0	0
43.09582	-85.7469	Alpine Township	0	0	0	0

Grand Rapids

Latitude	Longitude	Community	Scenario 1	2	3	4
43.0445	-85.6729	Comstock Park	0	0	0	0
43.1517	-85.7184	Sparta	0	0	0	0
43.12755	-85.561	Rockford	3	0	0	0
43.16745	-85.5019	Courtland Township	0	0	2	0
43.09593	-85.5884	Plainfield Charter Township	0	0	0	0
43.05888	-85.6277	Plainfield Charter Township	0	0	0	0
43.05046	-85.515	Cannon	0	0	0	0
43.02672	-85.7086	Walker	9	11	4	5
43.01314	-85.7498	Walker	0	0	0	0
42.94486	-85.7809	Walker	0	0	0	0
43.01391	-85.5685	Grand Rapids Charter Township	0	0	0	0
42.95753	-85.5567	Grand Rapids Charter Township	8	8	4	4
42.90323	-85.7011	Wyoming	0	0	0	0
42.91875	-85.7183	Wyoming	0	0	0	0
42.93065	-85.6961	Wyoming	12	13	5	6
42.92079	-85.7003	Wyoming	0	0	0	0
42.90637	-85.7114	Wyoming	0	0	0	0
42.90519	-85.6736	Wyoming	0	0	0	0
42.8892	-85.7081	Wyoming	0	0	0	0
42.88855	-85.6983	Wyoming	0	0	0	0
42.88938	-85.6515	Wyoming	0	0	0	0
42.87493	-85.7054	Wyoming	11	12	4	5
42.9225	-85.7501	Grandville	0	0	0	0
42.89887	-85.7763	Grandville	6	7	3	3
42.901	-85.7407	Grandville	0	0	0	0
42.87851	-85.6363	Kentwood	6	6	2	0
42.88013	-85.6486	Kentwood	0	0	0	0
42.8618	-85.6092	Kentwood	5	6	3	3
42.90264	-85.5735	Kentwood	0	0	3	4
42.929	-85.534	Cascade Township	0	0	0	0
42.91358	-85.469	Cascade Township	7	8	3	3
42.99463	-85.453	Ada Township	0	4	0	0
42.90252	-85.4159	Lowell Charter Township	0	0	0	0
42.84671	-85.6696	Cutlerville	0	0	0	0
42.82787	-85.6085	Caledonia Township	0	0	0	0

Grand Rapids

Latitude	Longitude	Community	Scenario 1	2	3	4
42.83801	-85.7527	Byron Township	0	0	0	0
42.78772	-85.7635	Byron Township	0	0	0	0
42.82246	-85.4739	Caledonia Township	0	0	0	0
43.09211	-85.8575	Polkton Charter Twp	0	0	0	0
43.01924	-85.816	Tallmadge Charter Township	0	0	0	0
42.85359	-85.8764	Hudsonville	0	0	0	0
42.90885	-85.878	Georgetown Twp	0	0	0	0
42.90876	-85.8275	Georgetown Twp	0	0	0	0
42.89614	-85.7917	Georgetown Twp	0	0	0	0
42.83717	-85.8144	Jamestown Charter Township	0	0	0	0

Detroit

Latitude	Longitude	Community	Scenario 1	2	3	4
42.58671	-82.8687	Mt Clemens	0	0	0	0
42.60392	-82.8926	Mt Clemens	8	9	4	4
42.62153	-82.901	Clinton Twp	0	0	0	0
42.58347	-82.9217	Clinton Twp	0	0	0	0
42.57566	-82.8747	Clinton Twp	6	8	0	0
42.55675	-82.9145	Clinton Twp	13	16	5	6
42.56275	-82.878	Clinton Twp	0	0	0	0
42.61212	-82.8382	Harrison Charter Township	0	0	0	0
42.58563	-82.8338	Harrison Charter Township	0	0	0	0
42.63119	-83.0264	Utica	0	0	0	0
42.63144	-83.0622	Shelby Charter Township	0	17	0	0
42.61625	-83.0809	Sterling Heights	0	0	0	0
42.60121	-83.0145	Sterling Heights	0	0	0	0
42.58052	-83.0185	Sterling Heights	6	0	0	0
42.55449	-83.0749	Sterling Heights	0	0	0	0
42.54245	-83.0157	Sterling Heights	0	0	0	0
42.5421	-82.9811	Sterling Heights	8	0	4	4
42.4862	-83.034	Center Line	0	0	0	0
42.5111	-83.0681	Warren	0	0	0	0
42.51102	-83.0231	Warren	0	0	0	0
42.51505	-82.9725	Warren	0	0	0	0
42.49258	-83.0554	Warren	0	0	0	0
42.49494	-82.9898	Warren	11	14	5	6
42.45777	-83.0654	Warren	0	0	0	0
42.46508	-83.0106	Warren	0	0	0	0
42.4546	-82.9742	Warren	8	9	4	4
42.48878	-82.9565	Roseville	0	0	0	0
42.51779	-82.9331	Roseville	0	0	0	0
42.50433	-82.9478	Roseville	0	0	0	0
42.53507	-82.9593	Fraser	0	0	0	0
42.47368	-82.9598	Eastpointe	0	0	0	0
42.47358	-82.9405	Eastpointe	0	0	0	0
42.53542	-82.8891	St Clair Shores	0	0	0	0
42.51922	-82.8951	St Clair Shores	10	0	4	0
42.49015	-82.9048	St Clair Shores	12	15	5	6
42.45257	-82.9037	St Clair Shores	0	0	0	0
42.0397	-83.3693	Ash Township	0	0	0	0

Detroit

Latitude	Longitude	Community	Scenario 1	2	3	4
42.06429	-83.2718	Berlin Charter Twp	0	0	0	0
41.98012	-83.2533	Berlin Charter Twp	4	4	0	0
41.97526	-83.3276	Berlin Charter Twp	0	0	0	0
42.64821	-83.2806	Pontiac	0	0	0	0
42.6861	-83.318	Lake Angelus	7	10	3	0
42.67199	-83.2715	Pontiac	0	0	0	0
42.66082	-83.2658	Pontiac	0	0	0	0
42.66157	-83.3114	Pontiac	0	0	0	0
42.64777	-83.3155	Pontiac	0	12	0	3
42.6396	-83.2781	Pontiac	0	0	0	0
42.63174	-83.2588	Auburn Hills	10	14	4	4
42.62854	-83.3228	Pontiac	0	0	0	0
42.62496	-83.3046	Pontiac	0	0	0	0
42.61403	-83.2837	Pontiac	0	0	0	0
42.62603	-83.2782	Pontiac	0	0	0	0
42.63713	-83.455	White Lake Charter Township	0	0	0	0
42.63028	-83.3471	Waterford Twp	0	0	0	0
42.66624	-83.4158	Waterford Twp	0	6	0	0
42.67896	-83.4001	Waterford Twp	0	0	0	0
42.68266	-83.347	Waterford Twp	0	0	0	0
42.66149	-83.3619	Waterford Twp	0	0	4	0
42.64124	-83.4236	Waterford Twp	0	0	2	0
42.65116	-83.3479	Waterford Twp	10	0	0	5
42.62901	-83.3801	Waterford Twp	5	0	0	0
42.68869	-83.2717	Auburn Hills	0	0	0	0
42.62224	-83.233	Auburn Hills	0	0	0	0
42.67596	-83.1719	Rochester Hills	0	0	0	0
42.62361	-83.1978	Rochester Hills	0	0	0	0
42.64111	-83.1477	Rochester Hills	13	0	6	5
42.53558	-83.4889	Walled Lake	0	0	0	0
42.60159	-83.4717	Commerce Charter Twp	0	0	0	0
42.56636	-83.4523	Commerce Charter Twp	9	10	4	5
42.55567	-83.4974	Commerce Charter Twp	0	0	0	0
42.58869	-83.3783	Orchard Lake Village	0	0	0	0
42.61385	-83.3338	Sylvan Lake	0	0	0	0
42.60622	-83.4203	West Bloomfield Township	0	0	0	0

Detroit

Latitude	Longitude	Community	Scenario 1	2	3	4
42.57904	-83.4173	West Bloomfield Township	0	0	0	0
42.56292	-83.3765	West Bloomfield Township	0	0	0	0
42.56078	-83.3518	West Bloomfield Township	0	0	0	0
42.57053	-83.2564	Bloomfield Twp	0	0	0	0
42.59036	-83.3099	Bloomfield Twp	10	11	4	5
42.60364	-83.2137	Bloomfield Twp	0	0	0	0
42.55621	-83.3151	Bloomfield Twp	0	0	0	0
42.55665	-83.248	Bloomfield Twp	0	0	0	0
42.53493	-83.2338	Bloomfield Twp	0	0	0	0
42.5521	-83.1908	Birmingham	12	13	5	5
42.61135	-83.1123	Troy	0	0	0	0
42.59917	-83.1942	Troy	0	0	0	0
42.56881	-83.1901	Troy	0	0	0	0
42.5571	-83.1924	Troy	0	0	0	0
42.58153	-83.1031	Troy	9	0	0	4
42.54578	-83.1279	Troy	0	0	0	0
42.47576	-83.5072	Novi	0	0	0	0
42.44304	-83.4929	Northville	0	0	0	0
42.4649	-83.3612	Farmington Hills	0	0	0	0
42.51769	-83.4085	Farmington Hills	8	10	0	0
42.51799	-83.3692	Farmington Hills	10	0	5	0
42.50189	-83.3431	Farmington Hills	0	0	0	0
42.48708	-83.3342	Farmington Hills	0	0	0	0
42.453	-83.3939	Farmington Hills	9	10	4	5
42.44519	-83.3196	Farmington Hills	0	0	0	0
42.48507	-83.2428	Southfield	15	17	7	9
42.51397	-83.2083	Southfield	0	0	0	0
42.4972	-83.2092	Southfield	12	11	6	6
42.48193	-83.2908	Southfield	0	12	0	0
42.46708	-83.3015	Southfield	0	0	0	0
42.46115	-83.2168	Southfield	0	0	0	0
42.4565	-83.2293	Southfield	0	0	0	0
42.5275	-83.3129	Franklin	0	0	0	0
42.5281	-83.2437	Beverly Hills	0	0	0	0
42.49697	-83.2271	Lathrup Village	0	0	0	0
42.48894	-83.1332	Royal Oak Charter Twp	0	0	0	0
42.53071	-83.1834	Royal Oak Charter Twp	0	0	0	0

Detroit

Latitude	Longitude	Community	Scenario 1	2	3	4
42.51104	-83.1567	Royal Oak Charter Twp	0	0	0	0
42.50838	-83.1348	Royal Oak Charter Twp	0	0	0	0
42.49877	-83.1336	Royal Oak Charter Twp	0	0	0	0
42.48318	-83.1175	Royal Oak Charter Twp	0	0	0	0
42.54008	-83.163	Clawson	12	16	6	5
42.49425	-83.1957	Berkley	0	0	0	0
42.48585	-83.1696	Huntington Woods	0	0	0	0
42.51049	-83.0931	Madison Heights	11	13	5	4
42.49356	-83.1119	Madison Heights	0	0	0	0
42.47943	-83.0994	Madison Heights	16	18	8	8
42.46535	-83.1876	Royal Oak Charter Twp	12	15	0	0
42.46728	-83.1708	Royal Oak Charter Twp	0	0	0	0
42.45312	-83.1684	Royal Oak Charter Twp	0	0	0	0
42.44914	-83.1492	Ferndale	0	0	0	0
42.45648	-83.1145	Ferndale	0	0	0	0
42.4669	-83.1004	Hazel Park	16	23	9	10
42.45601	-83.089	Hazel Park	0	0	0	0
42.33591	-83.054	Detroit	0	0	0	0
42.40661	-83.1086	Highland Park	0	13	0	0
42.40473	-83.087	Highland Park	11	0	6	6
42.42722	-83.1279	Detroit	0	0	0	0
42.42313	-83.1045	Detroit	14	0	6	0
42.39923	-83.1371	Detroit	12	0	0	6
42.39252	-83.1442	Detroit	0	0	0	0
42.37255	-83.1343	Detroit	10	0	4	0
42.38428	-83.1248	Detroit	0	0	0	0
42.37238	-83.1248	Detroit	0	0	0	0
42.38426	-83.1018	Detroit	0	0	0	0
42.38756	-83.0778	Detroit	0	0	0	0
42.35421	-83.1447	Detroit	0	0	0	0
42.36527	-83.1192	Detroit	0	0	0	0
42.36467	-83.1103	Detroit	0	0	0	0
42.36954	-83.0891	Detroit	8	14	4	5
42.37655	-83.0707	Detroit	0	0	0	0
42.34684	-83.1458	Detroit	0	0	0	0
42.35045	-83.1192	Detroit	0	0	0	0
42.35208	-83.0872	Detroit	0	0	0	0

Detroit

Latitude	Longitude	Community	Scenario 1	2	3	4
42.35612	-83.0714	Detroit	0	0	0	0
42.32859	-83.1354	Detroit	0	0	0	0
42.33628	-83.1146	Detroit	20	27	8	10
42.33995	-83.0957	Detroit	0	0	0	0
42.3414	-83.0849	Detroit	0	0	0	0
42.33972	-83.0586	Detroit	0	0	0	0
42.3082	-83.1134	Detroit	0	0	0	0
42.27355	-83.1487	Detroit	0	0	0	0
42.28384	-83.1289	Detroit	0	10	0	0
42.31225	-83.1191	Detroit	0	0	0	0
42.29508	-83.1111	Detroit	0	0	0	0
42.31364	-83.0987	Detroit	12	0	5	6
42.32703	-83.0752	Detroit	0	0	0	0
42.38	-83.1484	Detroit	0	0	0	0
42.43448	-83.2606	Detroit	0	0	0	0
42.43612	-83.2542	Detroit	0	0	0	0
42.41999	-83.2521	Detroit	0	12	4	0
42.43924	-83.2052	Detroit	0	0	0	0
42.44246	-83.1829	Detroit	0	0	0	0
42.40862	-83.1849	Detroit	0	0	0	0
42.43561	-83.1677	Detroit	0	0	0	0
42.42127	-83.1467	Detroit	0	0	0	0
42.40433	-83.2712	Detroit	0	0	0	0
42.38932	-83.2727	Detroit	0	0	0	0
42.40906	-83.254	Detroit	9	0	0	5
42.40374	-83.2329	Detroit	0	0	0	0
42.39863	-83.1842	Detroit	10	13	5	5
42.39984	-83.1485	Detroit	0	0	0	0
42.3837	-83.2311	Detroit	0	9	0	0
42.38791	-83.1664	Detroit	0	0	0	0
42.35903	-83.2522	Detroit	0	0	0	0
42.37054	-83.2131	Detroit	0	0	0	0
42.36247	-83.2344	Detroit	0	0	0	0
42.35309	-83.1913	Detroit	0	0	0	0
42.35478	-83.1522	Detroit	0	0	0	0
42.33327	-83.2311	Detroit	0	0	0	0
42.39181	-83.0163	Detroit	9	0	0	0

Detroit

Latitude	Longitude	Community	Scenario 1	2	3	4
42.38799	-83.0493	Hamtramck	0	0	0	0
42.44044	-83.0913	Detroit	8	0	0	0
42.43853	-83.0609	Detroit	0	0	0	0
42.43784	-83.0506	Detroit	0	0	0	0
42.42456	-83.0343	Detroit	0	0	0	0
42.44589	-83.0004	Detroit	0	0	0	0
42.44285	-82.952	Detroit	0	0	0	0
42.42422	-82.9773	Detroit	0	0	0	0
42.41751	-82.95	Detroit	11	11	6	5
42.40534	-83.0717	Hamtramck	0	0	0	0
42.41056	-83.0514	Hamtramck	0	15	0	0
42.40448	-83.009	Detroit	0	0	0	0
42.40855	-82.9789	Detroit	0	0	0	0
42.41257	-82.9564	Detroit	0	0	0	0
42.39547	-82.9369	Detroit	0	0	0	0
42.38617	-83.0359	Detroit	0	0	0	0
42.3981	-82.9752	Detroit	0	0	0	0
42.36734	-83.0481	Detroit	0	0	0	0
42.34602	-83.0412	Detroit	0	0	0	0
42.37355	-83.0366	Detroit	0	0	0	0
42.36211	-82.9942	Detroit	0	0	3	0
42.36878	-82.9846	Detroit	8	9	0	4
42.37714	-82.9586	Detroit	0	0	0	0
42.37611	-82.9513	Detroit	5	0	0	0
42.34462	-83.0291	Detroit	0	0	0	0
42.33821	-82.9929	Detroit	0	0	0	0
42.362	-82.9681	Detroit	0	0	0	0
42.362	-82.9493	Detroit	0	0	0	0
42.40409	-82.9101	Grosse Pointe Farms	0	7	0	0
42.43241	-82.9316	Harper Woods	0	0	0	0
42.43442	-82.8882	Grosse Pointe Woods	0	0	0	0
42.42917	-82.8824	Grosse Pointe Shores	0	0	0	0
42.39247	-82.9078	Grosse Pointe	0	0	0	0
42.38421	-82.9331	Grosse Pointe Park	0	0	0	0
42.35511	-83.4059	Livonia	10	0	0	0
42.41678	-83.3925	Livonia	0	0	0	0
42.41458	-83.3516	Livonia	0	0	0	5

Detroit

Latitude	Longitude	Community	Scenario 1	2	3	4
42.40473	-83.4059	Livonia	0	0	0	0
42.40539	-83.3899	Livonia	12	13	4	5
42.40808	-83.3498	Livonia	10	11	4	0
42.35769	-83.3658	Livonia	0	0	0	0
42.359	-83.3495	Livonia	12	19	8	8
42.42852	-83.4918	Northville	6	7	3	3
42.40696	-83.4951	Plymouth Charter Twp	0	0	0	0
42.37575	-83.475	Plymouth Charter Twp	0	0	0	0
42.37533	-83.4892	Plymouth Charter Twp	0	0	0	0
42.36654	-83.4447	Plymouth Charter Twp	12	0	0	5
42.40838	-83.3109	Redford Charter Twp	0	8	0	0
42.43493	-83.2912	Redford Charter Twp	13	0	5	0
42.4183	-83.3094	Redford Charter Twp	11	0	4	0
42.398	-83.3043	Redford Charter Twp	0	0	0	0
42.36022	-83.3087	Redford Charter Twp	0	0	0	0
42.3604	-83.2884	Redford Charter Twp	0	0	0	0
42.32924	-83.4192	Westland	0	0	0	0
42.34729	-83.3485	Westland	0	0	0	0
42.30397	-83.4095	Westland	0	17	7	6
42.30728	-83.3652	Westland	0	0	0	0
42.31716	-83.4718	Canton	0	0	0	0
42.3142	-83.3675	Garden City	0	0	0	0
42.3166	-83.3352	Garden City	0	0	0	0
42.32898	-83.3264	Garden City	0	0	0	0
42.26825	-83.403	Wayne	0	0	0	0
42.27106	-83.37	Wayne	14	12	5	5
42.30077	-83.3363	Inkster	0	0	0	0
42.29994	-83.3232	Inkster	0	0	0	0
42.28291	-83.3054	Inkster	0	0	0	0
42.28747	-83.2671	Dearborn	13	15	5	6
42.31324	-83.277	Dearborn	0	0	0	0
42.31192	-83.2418	Dearborn	0	0	0	0
42.32432	-83.1861	Dearborn	0	0	0	0
42.34814	-83.1857	Dearborn	11	13	5	6
42.33431	-83.1677	Dearborn	0	0	0	0
42.31438	-83.1488	Dearborn	0	0	0	0
42.30589	-83.1652	Dearborn	0	0	0	0

Detroit

Latitude	Longitude	Community	Scenario 1	2	3	4
42.28978	-83.2126	Dearborn	0	0	0	0
42.35004	-83.2857	Dearborn	0	0	0	0
42.3501	-83.3034	Dearborn	7	0	0	0
42.32933	-83.2582	Dearborn	0	0	0	0
42.31502	-83.2962	Dearborn	0	0	0	0
42.28038	-83.2805	Dearborn	0	0	0	0
42.27413	-83.2444	Dearborn	0	0	0	0
42.23435	-83.4121	Romulus	0	0	0	0
42.25701	-83.3511	Romulus	0	0	0	0
42.21024	-83.373	Romulus	0	0	0	0
42.23564	-83.2473	Taylor	0	0	0	0
42.24546	-83.2972	Taylor	0	0	0	0
42.24693	-83.258	Taylor	9	11	5	6
42.24598	-83.2451	Taylor	9	0	0	0
42.2092	-83.2364	Taylor	11	0	0	0
42.26452	-83.1788	Lincoln Park	9	0	5	0
42.23778	-83.1698	Lincoln Park	0	0	0	0
42.23541	-83.1856	Lincoln Park	0	0	0	0
42.22626	-83.1736	Lincoln Park	0	0	0	0
42.28829	-83.1843	Melvindale	0	0	0	0
42.26873	-83.1228	River Rouge	0	0	0	0
42.25332	-83.129	Ecorse	0	0	0	0
42.28266	-83.2015	Allen Park	0	0	0	0
42.2447	-83.2234	Allen Park	0	0	0	0
42.23787	-83.2183	Allen Park	0	16	0	0
42.20457	-83.2151	Southgate	0	0	0	0
42.18588	-83.2126	Southgate	0	0	0	0
42.20804	-83.1872	Southgate	6	7	0	4
42.2175	-83.1701	Wyandotte	0	0	0	0
42.18953	-83.1763	Wyandotte	0	0	0	0
42.19561	-83.1611	Wyandotte	0	0	0	0
42.1471	-83.2103	Trenton	0	0	0	0
42.14466	-83.1834	Trenton	0	0	0	0
42.14627	-83.1575	Grosse Ile Township	0	0	0	0
42.14777	-83.3905	Huron Charter Twp	0	0	0	0
42.15746	-83.3518	Huron Charter Twp	8	8	4	0
42.17199	-83.2111	Riverview	14	16	8	9

Detroit

			Scenario			
Latitude	Longitude	Community	1	2	3	4
42.12275	-83.2295	Woodhaven	0	0	0	0
42.14916	-83.296	Brownstown Charter Twp	0	0	0	0
42.05708	-83.1979	Brownstown Charter Twp	0	0	0	0
42.10348	-83.2667	Flat Rock	0	0	0	0
42.06904	-83.2351	Rockwood	0	0	0	0